Development of Lake Washington PCB Fate and Bioaccumulation Models

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Prepared for:

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- Fred Bergdolt, WA Dept. of Transportation
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EXECUTIVE SUMMARY

Washington Department of Health issued a fish consumption advisory for Lake Washington due to PCBs in 2006 (WADOH 2004) because they determined Lake Washington fish are contaminated with PCBs at levels unsafe for human consumption. To address this fish advisory, King County proposed and was awarded a U.S. Environmental Protection Agency (USEPA) Puget Sound Scientific Studies and Technical Investigations Assistance Grant in 2010 to 1) estimate loading of polychlorinated biphenyls (PCBs) and polybrominated diphenylethers (PBDEs) to Lake Washington, Lake Union and Puget Sound and 2) model the potential decrease in Lake Washington fish tissue concentrations associated with select PCB loading reduction scenarios. The overall project is considered a first step toward understanding the relative importance of major contaminant loading pathways that contribute PCBs to these lakes, as well as understanding their long term fate and the potential recovery.

The primary goal of this project is to develop a more complete understanding of the processes controlling the ultimate fate of PCBs and to inform management actions to reduce health risks from consuming PCB-contaminated fish from Lake Washington. The study will also provide a better understanding on which to develop future monitoring and modeling efforts needed to fully address the issue of human health risks from PCB-contaminated fish in Lake Washington. This report describes in detail one component of this project: the development of a fate model and a bioaccumulation model for PCBs in Lake Washington.

This report describes the development of total PCB (tPCB) fate and bioaccumulation models for Lake Washington and evaluates how well the models perform. It also describes the results of sensitivity and uncertainty analyses. The fate model uses chemical and Lake Washington information to predict Lake Washington water and sediment concentrations of tPCB. The bioaccumulation model uses chemical and Lake Washington food web information to predict concentrations in fish tissue. Although loading estimates were developed for PBDEs, development of fate and bioaccumulation models for PBDEs was outside the scope of this project.[1]

The results of the fate and bioaccumulation model development and testing are as follows.

- The fate model predicted water and sediment concentrations from estimates of current loadings well when compared to observed water and sediment concentrations. The model testing supports the assumptions made to develop the fate model, but most importantly, supports the tPCB loading estimate derived as part of this study as a reliable first-approximation of the current tPCB loading rate to the lake.

[1] The fate and bioaccumulation models were intended to answer questions pertaining to the PCB fish consumption advisory. Currently, there is no PBDE fish consumption advisory for Lake Washington. Thus, the scope was limited to PCBs only.

- Model results suggest that the response time necessary for Lake Washington sediment and water concentrations to reach equilibrium with a constant load is approximately 40 years. The most rapid change in concentrations occurs in the first 20 years. Thus, this suggests any changes reducing PCB load to Lake Washington will require several decades to be fully reflected in fish tissues.
- Tissue concentrations predicted using water and sediment tPCB concentrations from field data compared to those using the fate model output demonstrated good performance of the bioaccumulation model with both, but better performance using the sediment and water concentrations predicted by the fate model.[2]
- Testing indicated the fate and bioaccumulation models performed well and similarly to applications of this model in San Francisco Bay, Georgia Basin and Puget Sound.

In conclusion, the fate and bioaccumulation models were successfully developed for application in this project to Lake Washington. In the next phase of this project, the fate and bioaccumulation models will be coupled to evaluate total tPCB loading reduction scenarios to inform water quality managers and stakeholders on the magnitude of change required to reach safe PCB tissue levels in Lake Washington fish. The results of these model simulations, along with a review of project findings and overall recommendations for future work, will be presented in a separate and final report for this project.

[2] Field data were likely biased high because sampling often focused on areas suspected of contamination (e.g., near combined sewer overflows or storm drains) and included samples that represented up to 10 cm of surface sediment, which potentially includes higher tPCB concentrations that occurred in sediments deposited in the 1970s. Because of this bias and better model fit of the fate model predicted sediment and water concentrations, the latter source was selected for use in model application occurring later in the project.

1.0 INTRODUCTION

Polychlorinated biphenyls (PCBs) are present in Lake Washington fish at levels unsafe for human consumption (WADOH 2004). In addition, a similarly persistent and more modern chemical, polybrominated diphenyl ethers (PBDEs) is also bioaccumulating in Lake Washington fish. Elevated concentrations of PCBs and PBDEs are not unique to Lake Washington, as evidenced by chemical concentrations measured in marine mammal and fish tissue from Puget Sound (Ross et al. 2000, Ross et al. 2004, Krahn et al. 2007, West et al. 2008, Sloan et al. 2010, Cullon et al. 2005). However, to date there have not been any studies focused on how these chemicals are getting into Lake Washington fish or the quantity of these chemicals entering Lake Washington, Lake Union and the Ship Canal (Lake Union), and Puget Sound from this watershed. Primary goals of this project are to help fill PCB and PBDE data gaps for the Lake Washington watershed and Puget Sound basin and provide information and tools needed to direct management of PCBs and reduce health risks associated with Lake Washington fish consumption.

This project is considered a first step toward understanding the relative importance of major contaminant loading pathways that contribute PCBs and PBDEs to these lakes, as well as understanding their long term fate and the potential for recovery. The end result of this project is expected to be a more complete understanding of the processes controlling the ultimate fate and the potential for management actions to reduce health risks associated with consuming PCB-contaminated fish from Lake Washington. The project will also provide a better understanding on which to develop future monitoring and modeling efforts.

Specifically, King County was awarded a U.S. Environmental Protection Agency (USEPA) Puget Sound Science Studies and Technical Investigation Assistance Grant in 2010 to 1) estimate loading of PCBs and PBDEs to Lake Washington, Lake Union and Puget Sound and 2) model the potential reduction in Lake Washington fish tissue concentrations associated with select PCB loading reduction scenarios. Other components of the project that have been completed before this report include a field study in 2011 and 2012 (King County 2013a) and PCB/PBDE loadings estimates (King County 2013b). The field study measured PCB and PBDE concentrations in key contaminant loading pathways to Lakes Washington and Union and in the export pathway leaving the lake system through the Hiram M. Chittenden Locks to Puget Sound. The loading pathways sampled included rivers, streams, stormwater, combined sewer overflows, highway bridges, and atmospheric deposition. For the loadings estimation, contaminant concentration data for these pathways were combined with long term flow estimates to develop mass loading estimates to Lakes Washington and Union, and subsequent export to Puget Sound for total PCB (tPCB) and total PBDE (tPBDE).

This report describes the development of tPCB mass balance (fate) and bioaccumulation models for Lake Washington as well as model sensitivity, uncertainty and performance.

Although PBDE loading estimates were developed, including this compound in the fate and bioaccumulation models was outside the scope of the project.[3]

1.1 Problem Definition and Background

PCBs are chlorinated organic compounds that were manufactured for uses that required chemical stability and low flammability. Commercial PCBs were originally produced in North America as mixtures "Aroclors®" by the manufacturer Monsanto. Specific Aroclor® mixtures were named using a four-digit number; the first two digits represent the number of carbon molecules, while the second two digits refer to the percent chlorination by weight (e.g., Aroclor® 1016, Aroclor® 1254) (EPA 2013). PCBs include 209 individual compounds known as congeners that vary to some degree in physical, chemical and toxicological properties based primarily on the degree of chlorination. Due to their chemical stability and low water solubility, PCBs are persistent in the environment, bind strongly to sediment and soil particles, and bioaccumulate in aquatic organisms, wildlife, and humans.

The bioaccumulation of PCBs presents a potential health risk to aquatic life, terrestrial wildlife, and humans. In 2004, the Washington Department of Health (WADOH) issued a fish consumption advisory for PCBs in Lake Washington for yellow perch, cutthroat trout, carp and northern pikeminnow (WADOH 2004).[4] PCB concentrations in Lake Washington fish exceed both the National Toxics Rule[5] levels for protection of human health and the 95th-percentile of concentrations measured in fish collected statewide (Seiders and Deligeannis 2007).

Commercial production of PCBs began in the 1920s, initially for use as a dielectric fluid in electrical transformers, capacitors, and electric motors. After World War II, production increased substantially and PCB use diversified to include heat transfer fluids, hydraulic fluids, plasticizers, carbonless copy paper, lubricants, inks, laminating agents, paints, adhesives, waxes, additives in cements and plasters, casting agents, sealing liquids, fire retardants, immersion oils and pesticides (De Voogt and Brinkman 1989). PCBs were voluntarily phased-out of production in the 1970s and in the United States manufacture and most uses were banned in 1979 (44 FR 31514).[6] While the sale and production of PCBs have been banned for over three decades, considerable amounts of PCBs remain in use – primarily as dielectric fluid in "closed sources" such as transformers and capacitors and in "open sources" such as building caulks and sealants in older structures (Diamond et al. 2010; Robson et al. 2010).

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[3] The fate and bioaccumulation models were intended to answer questions pertaining to the fish consumption advisory for PCBs. Currently, there is no fish consumption advisory for PBDEs on Lake Washington. Thus, the modeling scope was limited to PCBs only.

[4] Washington State Department of Health Fish Consumption Advisories (see: http://www.doh.wa.gov/CommunityandEnvironment/Food/Fish/Advisories.aspx

[5] U.S. Environmental Protection Agency (USEPA) National Toxics Rule (see: http://water.epa.gov/scitech/swguidance/standards/wqsregs.cfm)

[6] U.S. Environmental Protection Agency (see: http://www.epa.gov/history/topics/pcbs/01.html)

In general, halting PCB production, elimination of many uses, and a declining inventory of PCBs in use has resulted in decreasing concentrations in environmental media, including fish tissue and sediments (Peterman et al. 1990; Van Metre and Mahler 2005). However, studies of fish tissue and sediment concentrations in many areas of the world indicate that the initial rate of decline appears to have slowed or halted completely (Van Metre et al. 1998; Hickey et al. 2006; Bhavsar et al. 2007).

Historical data on PCB levels in non-anadromous fish collected from Lakes Washington and Union are insufficient to evaluate long-term trends in PCB concentrations (McIntyre 2004). While anadromous fish have been studied, these fish generally spend only a portion of their life cycle in these lakes and measured contaminant concentrations are generally lower than those observed in resident (non-anadromous) fish species (McIntyre 2004; Fletcher 2009).

A substantial decline in sediment PCB concentrations in Lake Washington has been documented; levels are now about a third or less of the peak concentrations measured in the early 1970s (Yake 2001; Van Metre et al. 2004; Van Metre and Mahler 2005; Furl et al. 2009 Era-Miller et al. 2010). Van Metre and Mahler (2005) collected and dated one core from the central basin of Lake Washington. They reported a median concentration of 199 µg/kg dw for the 1965-1975 period and 59 µg/kg dw for the 1990-2000 period. The increase and subsequent decrease in sediment PCB concentrations coincide with national trends in production, use and subsequent use limitations and elimination of production. In the case of Lake Washington, the increase and decline also coincides generally with the development and growth of cities around the lake and the subsequent diversion of treated wastewater from Lake Washington to Puget Sound that was completed in 1968 (Edmondson and Lehman 1981).

1.2 Project Goals and Objectives

The overall project is intended to engage in the first efforts to understand why PCBs are accumulating in Lake Washington fish and identify actions that may address this problem. Specifically, this project will fill data gaps and develop modeling tools to help answer three management questions:

1. Which types of loading pathways are the highest priorities for PCB/PBDE load reduction?
2. Will potential loading reductions from these pathways reduce chemical bioaccumulation in fish, and contribute substantially towards lifting the fish consumption advisory on Lake Washington?
3. How long might it take the system to respond to these hypothetical loading reductions?

This report describes the development and testing of coupled models to estimate contaminant fate and bioaccumulation of PCBs in Lake Washington.

1.3 Modeling Objectives

The ultimate goal of the development of fate and bioaccumulation models for Lake Washington is to reliably forecast the reduction of PCB concentrations in fish tissue under a variety of possible water quality management scenarios. This effort is considered to be a multi-phased process in which the development of a relatively simple mass budget fate model coupled to an ecosystem bioaccumulation model is a first step. While this first step will be accomplished during the grant project period the remaining phases are expected to occur beyond this period.

The specific objectives of the modeling effort are as follows:

- Develop a quantitative understanding of the long-term fate of PCBs in Lake Washington.
- Provide quantitative estimates of the time and magnitude of the response of lake water, sediment and fish tissue to reductions in PCB loading.

These two modeling objectives address overall project study questions 2 and 3 above.

2.0 STUDY AREA AND MODEL DOMAIN

The study area is the Lake Washington watershed and encompasses 1,550 km^2 (598 mi^2) defined by the Lake Washington outlet at Montlake Cut (Figure 1).[7] The area experiences a generally mild maritime climate with heaviest precipitation occurring in winter months, primarily as rain at lower elevations and as snow at higher elevations. Elevations are generally less than 1,000 m (3,281 ft); however, total annual rainfall is very dependent on elevation which ranges from about 6 m above mean sea level (msl) to 1,700 m (4,464 ft). The variation in elevation results in a range of annual precipitation from almost 1,000 mm (39 in) at lake level to over 2,500 mm (100 in) at the highest elevations. Winds are highly variable, but during the winter, major storms and associated winds typically originate from the southwest.

Two major rivers drain to Lake Washington. The Sammamish River drains Lake Sammamish and tributaries in the Sammamish River valley and enters Lake Washington from the north, providing about 30 percent of the total inflow to the Lake. The Cedar River enters the south end of the lake and contributes about 50 percent of the total inflow (Edmondson 1977; King County 2003; Cerco et al. 2004). The remainder of the inflow comes from a number of creeks and small tributary basins that drain directly to the lake. Lake Washington then drains through the Montlake Cut to Lake Union, which drains through the Lake Washington Ship Canal (Ship Canal) and Locks to Puget Sound.

Historically, Lakes Washington and Union were not connected. By 1916, a canal was completed between the two lakes, the outlet of Lake Union was widened and deepened and a lock and dam system was in operation (Chrzastowski 1983). Prior to canal and lock construction, the main inflow to Lake Washington was from the Sammamish River and outflow was through the Black River at the southern end of the lake. To provide sufficient water for lock operation and to reduce flooding, the Cedar River, which had previously joined the Black River near the southern end of the lake, was diverted to Lake Washington (Chrzastowski 1983). These engineering changes resulted in the summer intrusion of saltwater from Puget Sound that enters through the Locks and Ship Canal into Lake Union, resulting in a layer of denser saline water at depth in the lake, which is then entrained and flushed from the lake during winter high flows. The extent of intrusion of saline water is limited to Lake Union through various mitigation measures, including a salt water barrier at the upstream side of the larger of the two locks and a saltwater drain located in a depression at the head of both locks. Salinity is monitored continuously in summer at the University Bridge and is not to exceed 1 ppt (173-201A WAC).

The immediate area around Lake Washington is highly developed and includes the major cities (i.e., >50,000 residents) of Seattle, Bellevue, and Renton. Although the discharge of municipal wastewater to Lake Washington was halted around 1968, there are still approximately 40 CSOs that intermittently discharge to locations along the Seattle

[7] This watershed area estimate includes the surfaces of all lakes, streams and wetlands in the watershed.

shoreline of the Lake. Lake Washington is crossed by two floating bridges – State Route 520 (SR 520) to the north and Interstate 90 (I-90) to the south.

The study area also includes relatively undeveloped, primarily forested, areas in the headwaters of the two major river basins. The headwaters of tributaries along the southeast shoreline of Lake Washington are also relatively undeveloped. The headwaters of the Cedar River are within a protected watershed for the Chester Morse water supply reservoir that provides Seattle Public Utilities (SPU) with a portion of its potable water supply.

Within the study area, the model domain is defined as Lake Washington, which is the second largest natural lake in the state. The lake is an elongated north-south trending glacial trough approximately 35 km (21.7 mi) long with an average depth of 32.9 m (108 ft), a maximum depth of 65.2 m (214 ft), a surface area of 87.6 km^2 (33.8 mi^2) and a volume of 2.884 x 10^9 m^3 (2,338,000 acre-ft) (Anderson 1954).[8] Edmondson and Lehman (1981) provide estimates of annual lake hydraulic renewal times, which indicate that on average the fraction of lake volume renewed each year with incoming water (corrected for evaporation) is 0.43 per year. The reciprocal of this is 2.3 years – the average hydraulic residence time of water in the lake.

[8] King County geographic information system (GIS) data indicate a lake surface area (including Union Bay) closer to 89 km^2 (34.4 mi^2), but this may be due to the exclusion of Union Bay from the earlier estimate. Also, Edmondson and Lehman (1981) report a total lake volume of 2.885 x 10^9 m^3 (2,339,000 acre-ft).

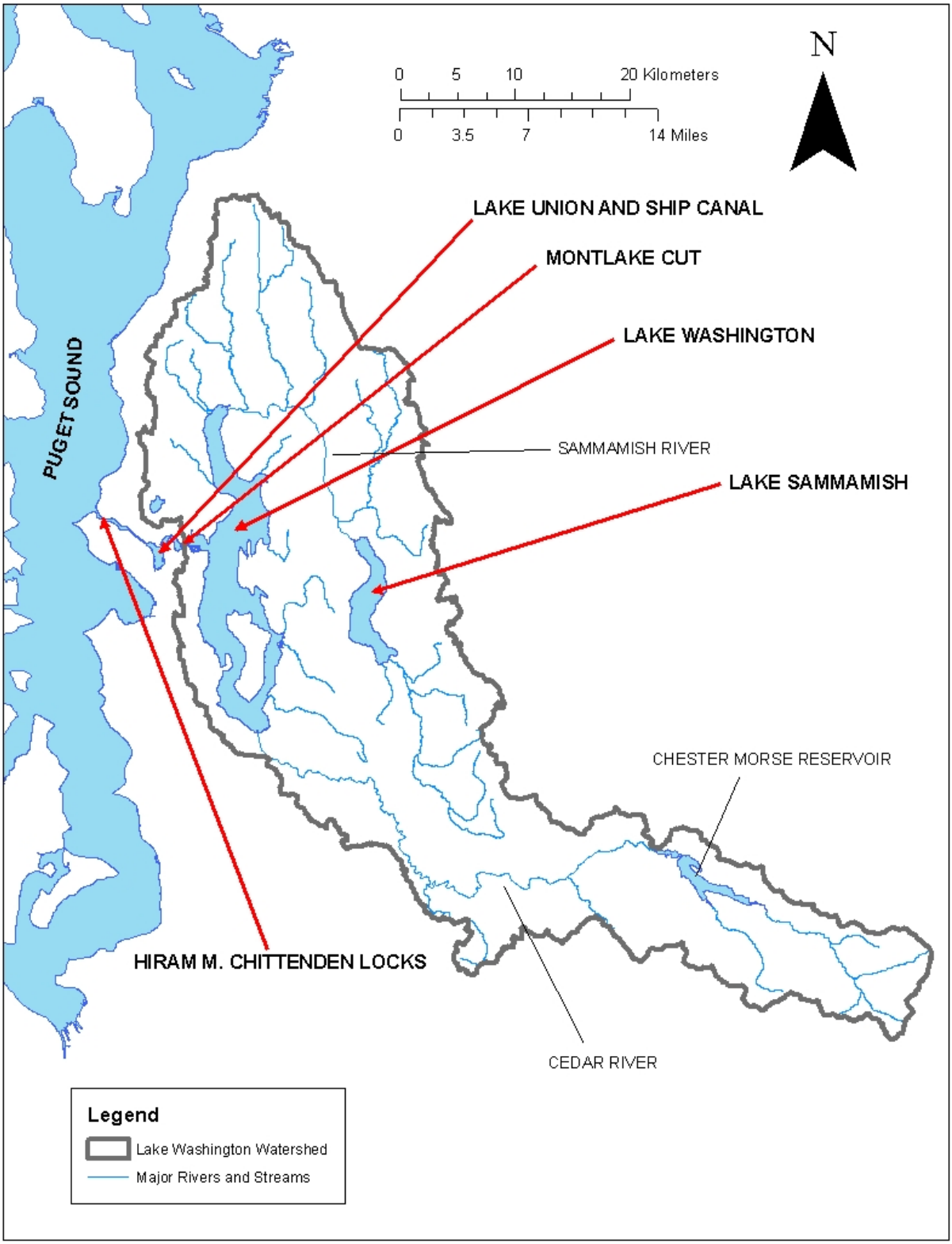

Figure 1. Lake Washington Watershed.

3.0 THE MODELS

Based on the model selection criteria presented in the Modeling Quality Assurance Project Plan (QAPP) developed for this study (King County 2013c), the contaminant fate and bioaccumulation modeling framework developed for San Francisco Bay (Davis et al. 2007) and modified for use in Puget Sound (Pelletier and Mohamedali 2009) was also adapted for use in this study.

As previously discussed, tPCBs encompass 209 congeners that vary widely in their chemical and toxicological properties. To simulate tPCBs, the framework for both the fate and bioaccumulation models allow for either (1) use of the chemical properties of a single congener to represent the entire chemical class, or (2) separate simulations of a number of different congeners or homologues which are then summed to determine the "total" result for the entire chemical class. Davis (2004) and Pelletier and Mohamedali (2009) used the first strategy to simulate mass fluxes of tPCBs according to the chemical properties of a single congener, PCB-118. PCB-118 was selected as the "representative" congener based on its intermediate chemical properties and level of chlorination (penta), abundance in the ecosystem, chemical similarity to the most toxic congener to humans (PCB-126), and data availability. The first strategy, use of a single congener, was used for development of the Lake Washington PCB fate model.

In contrast, the bioaccumulation model as employed by Condon (2007) and Pelletier and Mohamedali (2009) used the second strategy, simulating the movement of 57 different PCB congeners through the food web and then summing to get "total" concentrations for the various organisms. The modeled congeners were chosen based on their presence in regional sediment and biota and because those congeners were known to comprise the majority of the tPCB mass (and were thus considered to be reasonably representative of the behavior of the entire family of PCB congeners). However, PCBs have only been analyzed as Aroclors® in Lake Washington sediment and aside from four fish fillet samples[9], congener data are not available for biota. Therefore, the first strategy described above (e.g., chemical properties of a single congener) was used to develop the Lake Washington bioaccumulation model.

3.1 Contaminant Fate Model

The contaminant fate model is a two-compartment (lake water and bottom sediment) fate model described by Davis (2004). The steps required for development and testing of the model included the following:

- Compilation of water and sediment PCB data for Lake Washington provided the basis for testing model assumptions (current estimated loads and parameter values). As previously discussed, these data were collected as part of the Field Study Data Report and Data Report Sediment Addendum (King County 2013a and 2013d).

[9] Two samples were cutthroat trout, one was carp and one was northern pikeminnow.

- Set up and test the two-compartment box model developed for San Francisco Bay (Davis 2004) and adapted for Lake Washington.

Model testing was based on a hindcast modeling approach used in the development of the initial San Francisco Bay PBDE model (Oram et al. 2008). Fluvial and atmospheric loading estimates developed as part of this study (King County 2013b) provided the estimated current tPCB load for hindcast testing of the fate model.

3.2 Ecosystem Bioaccumulation Model

The bioaccumulation model was originally developed by Arnot and Gobas (2004), and adapted for use in San Francisco Bay (Gobas and Arnot 2005). The San Francisco Bay bioaccumulation model was also adapted for use in modeling contaminant accumulation in biota at various trophic levels within the Strait of Georgia (Condon 2007) and subsequently for select Puget Sound biota (Pelletier and Mohamedali 2009).

The model predicts whole body contaminant concentrations in food web components (e.g., phytoplankton, zooplankton, benthic invertebrates, and fish) by calculating chemical uptake from ingestion and respiration as well as elimination from respiration, egestion, metabolism, and growth dilution. The model assumes steady-state conditions; i.e., the chemical concentrations have reached equilibrium in water, sediment, and biota. The main implication of this assumption is that predicted biota PCB concentrations are directly proportional to sediment and water concentrations at any point in time. This assumption is reasonable considering the rapid typical response time of organisms (days) to changes in external conditions (Gobas and Arnot 2010). In comparison, the response of sediment concentrations to a change in PCB load is slow (i.e., years).

The steps required to develop and test the Lake Washington bioaccumulation model included the following:

- Compile existing information on the food web structure of Lake Washington and develop a conceptual food web model using the selected taxa of interest.
- Compile data to establish reasonable model input values for model parameters (e.g., biota lipid content, concentration of suspended solids, organism wet weight).
- Compile PCB concentration data in Lake Washington biota to provide the basis for testing model assumptions.

Model testing was based on the approach used in development of the San Francisco Bay and Puget Sound models (Gobas and Arnot 2005, Davis et al. 2007, Pelletier and Mohamedali 2009). Available sediment, water column and biota tissue data for tPCB provided the basis for model testing. Fundamentally, the testing of the bioaccumulation model was based on comparison of model-predicted biota tPCB concentrations to observed tissue concentrations.

3.3 Data Requirements

A variety of environmental data served as inputs and boundary conditions for the models. The data required for model development and testing included physical, chemical, and

biological data. The types of data required, and sources, where known and/or applicable, are described below. The development of input data for each model is described in Sections 4.0 (Fate Model) and 5.0 (Bioaccumulation Model). The general types of data needed for model development are described below.

3.3.1 Physical

The fate model requires a variety of physical data including the lake volume and water and sediment surface areas. These physical measurements were obtained from published sources (see Section 4.0). Data for additional parameters included mean outflow rate and mean lake temperature, etc. Lake temperature is the only physical parameter in the bioaccumulation model. To the extent possible, model input values were derived from data found in published literature and supplemented with values published for other systems if local data were unavailable. Lake Washington has been the focus of scientific research for many years. Therefore, there is a wealth of published data was available for review to identify lake-specific sources of model inputs. For example, the mean outflow rate was based on the long-term (2002-2011) lake outflow rate derived by King County (2013b). Wakeham et al. (2004) and Furl et al. (2009) provided the most recent estimates of sediment burial rates.

3.3.2 Chemical

The fate and bioaccumulation models required a variety of ambient PCB data for water, sediment, and biota in Lake Washington, in addition to concentration data for suspended solids, particulate and dissolved organic carbon (DOC) in the water column, and sediment organic carbon content. The fate model also required long-term PCB loading estimates which were based on data collected as part of the project field study (King County 2013a). This field study also provided data on PCB source pathways to the lake, including CSOs, atmospheric deposition, and river and stream inputs which were used to develop current long-term (2002-2011) tPCB loading estimates to Lake Washington for use as inputs to the fate model (King County 2013b).

Summaries of available sediment PCB data for Lake Washington were found in Moshenberg (2004). Additional sediment PCB data were available from Ecology (e.g., Era-Miller et al. 2010) and King County (2008).

PCB data for Lake Washington biota were available from McIntyre (2004), Ecology (Johnson et al. 2006, Seiders and Deligeannis 2007) and King County (2013e). However, some of these data represented PCB concentrations in fillet tissue and could not be used; only whole body tissue data from McIntyre (2004) and King County (2013e) were used to test the model. Use of fillet tissue data would have required conversion to whole-body estimates and regression of empirical fillet and whole-body PCB concentrations to develop a predictive relationship. However, these types of data are not available for Lake Washington and the number of whole-body results was deemed adequate for model testing.

In addition to tPCB data, data for additional parameters (e.g., sediment organic carbon content, and suspended solids and organic carbon in water) were obtained primarily from

the King County Laboratory Information Management System (LIMS) environmental database that contains data generated by the King County Environmental Laboratory following project-specific QAPPs and published laboratory Standard Operating Procedures (SOPs).

3.3.3 Biological

A variety of biological data were required to develop the bioaccumulation model including food web structure and dietary fractions for the modeled taxonomic groups or taxa. The Lake Washington food web structure used in the bioaccumulation model was developed by starting with a simplified food web and expanding into a more detailed one based on information available from published studies examining the Lake Washington food web (McIntyre 2004, Mazur 2004) and dietary preferences (e.g., Brocksmith 1999, Fayram and Sibley 2000, McIntyre 2004, Tabor et al. 2004, Tabor et al. 2007). The simplified food web included major taxonomic groups: detritus, phytoplankton, zooplankton, benthic invertebrates, forage (herbivorous and omnivorous) fish, and piscivorous fish (Figure 2).

Once the conceptual food web model was established, information on dietary composition, solid and lipid content, and body weight were compiled from sources with a preference for Lake Washington specific data. When Lake Washington specific data were unavailable, assumptions guided by studies from other water bodies were made to select appropriate values.

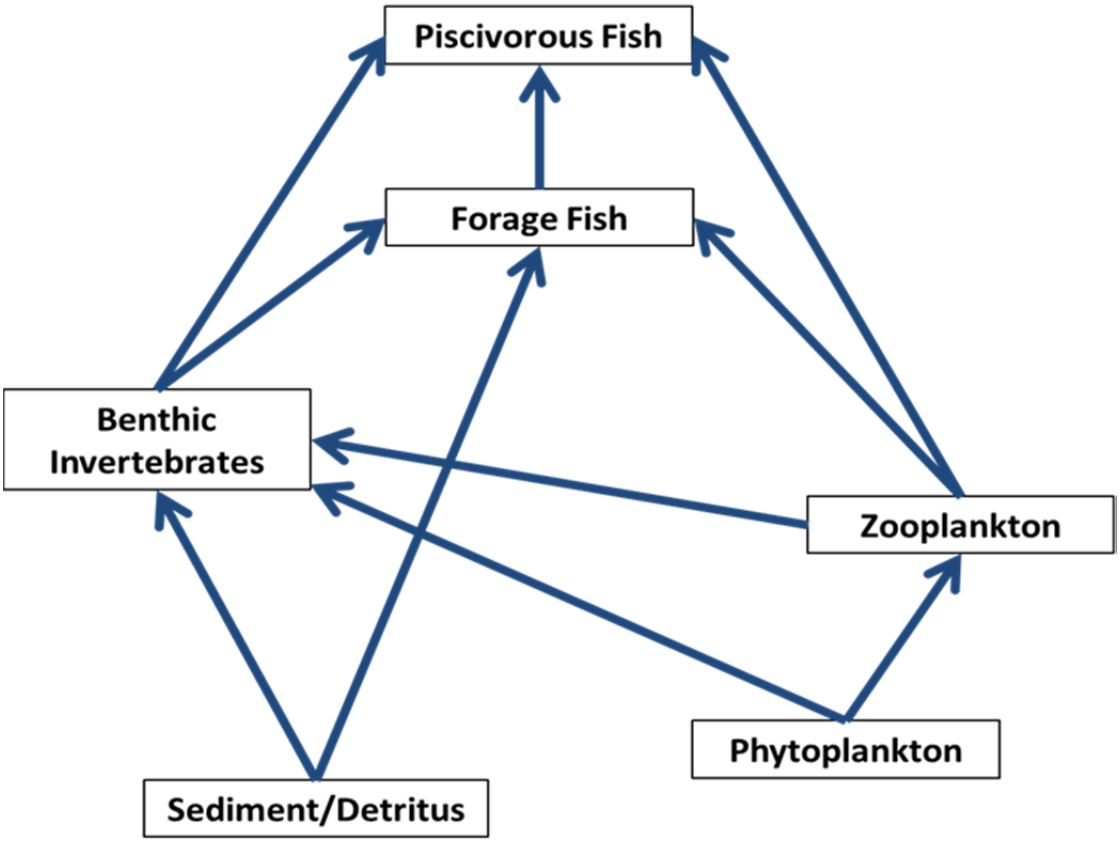

Figure 2. Simplified Food Web for Lake Washington

3.4 Data Acceptance Criteria and Rules

The following acceptance criteria were applied to all data used for model development and testing:

- *Data Reasonableness*. The quality of existing data was evaluated graphically and through review of available written reports. Data were assessed for model relevance and biased data points were removed, such as chemistry results from deep subsamples of sediment cores and tissue data from species not modeled.
- *Data Representativeness*. Data that were reasonably complete and representative of typical conditions at the location under consideration (e.g., model region, water column layer, and watershed) were used. Data from contaminated "hot spots" were included because they represented current conditions.
- *Data Comparability*. Long-term water quality monitoring programs often collect, handle, preserve, and analyze samples using methodologies that evolve over time, particularly for highly regulated or recently banned chemicals. In recent decades advances in analytical methods have improved the capability of detecting extremely low contaminant concentrations. Older PCB Aroclor® analytical methods frequently

resulted in non-detected concentrations, particularly for surface water, but with detection limits much higher than current state-of-the-art analytical methods. Best professional judgment was used to determine whether data from the various sources were comparable. The addenda to the study data report (King County 2013d and 2013e) detailed the assumptions that were made when using data collected with differing sampling or analysis techniques.

At least one Aroclor® or congener was detected in every water or sediment sample used for modeling (King County 2013a and 2013c). However, Aroclors® were not detected in some of the fish tissue samples. Due to the relatively small sample sizes (n<20) these samples were excluded from the data analysis because any substitution method (e.g., full or half the detection limit) was seen as presenting substantial bias to any calculated statistics. One exception to this rule was made when no detected PCB results for any samples of a species were available. In these cases, the highest detection limit of the non-detect results was used to provide some indication of the observed tissue concentration for model testing.

Summation of PCB congener and Aroclor® data into tPCB concentrations for use in model development and testing required development of summing rules that included rules developed above for handling non-detect data. In general, tPCB was calculated by summing the detected values as reported for individual congeners. Rules developed for summing PCB congeners or Aroclors® for existing data used in model development and testing were documented in the addenda to the study data report (King County 2013d and 2013e). Guidance in Pelletier and Mohamedali (2009) and Osterberg and Pelletier (2012) provided the foundation of the proposed approach.

It is acknowledged that PCB congener sums are generally considered more accurate than Aroclor® sums and that a sum of Aroclors® can over- or underestimate tPCBs. PCB congener and Aroclor® concentrations from split sediment or tissue samples from Lake Washington are not available to quantify this potential bias. However, comparisons of tPCBs based on congener and Aroclor® data for tissue in the Lower Duwamish Waterway Remedial Investigation (Windward 2010) and for sediment and tissue in the East Waterway Operable Unit Supplemental Draft Remedial Investigation/Feasibility Study (Windward and Anchor QEA 2012) concluded that the sums were similar; no consistency in over- or under-prediction was observed. For this project, it is assumed that differences in tPCB sums based on congeners and Aroclors® are not collectively significant.

3.5 Model Sensitivity and Uncertainty Assessments

To evaluate model performance and variability of results, sensitivity and uncertainty analyses were conducted. Uncertainty can arise from a number of sources that range from errors in the input data used to calibrate the model, to imprecise estimates for key parameters, to variations in how certain processes are parameterized in the model domain. Regardless of the underlying cause, it is good practice to evaluate these uncertainties and reduce them if possible (EPA 2009a, Taylor 1997, Beck 1987). By investigating the "relative sensitivity" of model parameters, a user can become knowledgeable of the relative importance of parameters in the model. By knowing the uncertainty associated with

parameter values and the sensitivity of the model to specific parameters, a user will be more informed regarding the confidence that can be placed in the model results (EPA 2009a).

Model *sensitivity* describes the degree to which results are affected by changes in selected inputs. Sensitivity analysis can help improve understanding of the relative importance of model parameters, identifying which parameters do not significantly affect model outputs and which parameters and processes strongly influence results.

Model *uncertainty* is used to describe incomplete or imperfect knowledge about parameters, data and assumptions. Uncertainty can arise from many sources, including measurement and analytical errors for model input data and imprecise estimates for key parameters. Uncertainty analyses investigate how the model results are affected by this lack of knowledge of the true values of certain inputs and parameters.

The details of the approach used to evaluate the sensitivity and uncertainty of the fate and bioaccumulation models are provided in Section 6.0.

4.0 FATE MODEL INPUT DATA

Mathematically, the fate model is comprised of two equations which determine the gains and losses of PCBs from the lake water and bottom sediment (Figure 3):

$$\Delta MW/\Delta t = L + k_{SW1}MS + k_{SW2}MS - k_V MW - k_O MW - k_{WR}MW - k_{WS1}MW - k_{WS2}MW \quad (1)$$

$$\Delta MS/\Delta t = k_{WS1}MW + k_{WS2}MW - k_{SW1}MS - k_{SW2}MS - k_B MS - k_{SR}MS \quad (2)$$

where,

MW = total mass of PCB in lake water

L = total external load of PCB to lake

MS = total mass of PCB in sediment

and the rate constants are defined in Table 1.

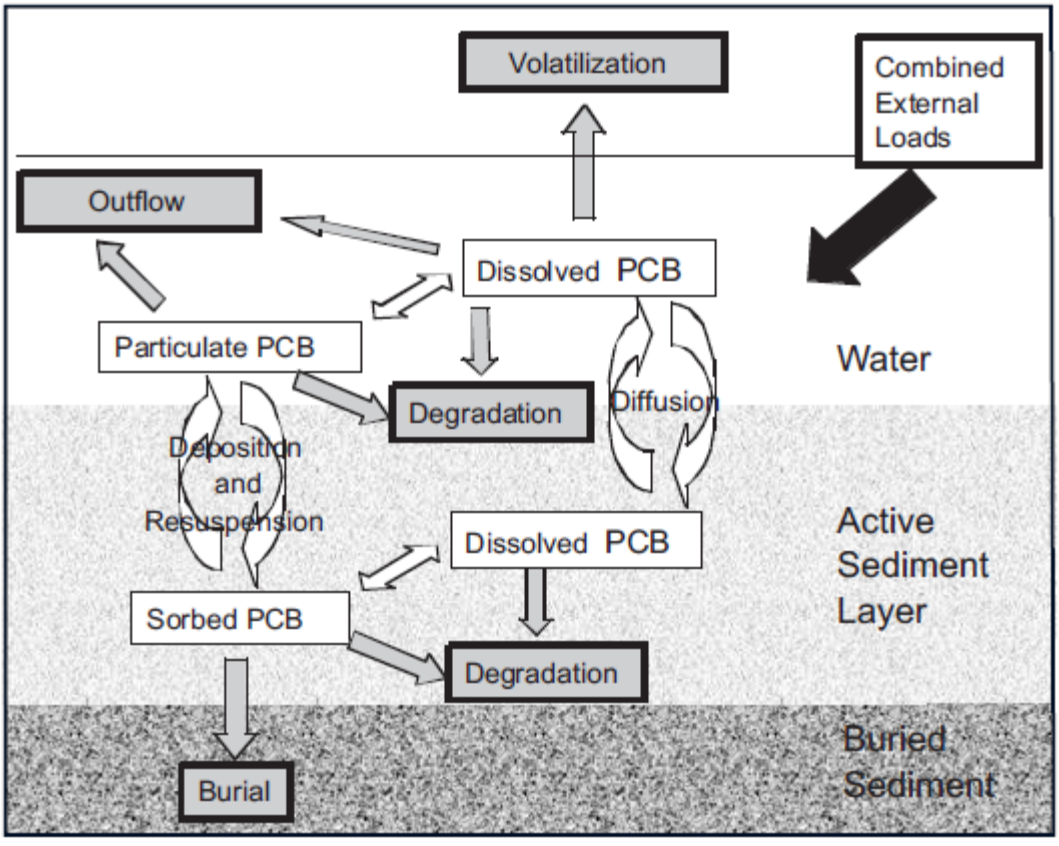

Figure 3. Diagram of PCB fate processes included in model. Source: Davis (2004).

Table 1. Rate constants (d^{-1}) for PCBs in Lake Washington based on best estimates of model input data. San Francisco Bay and Lake Ontario values included for comparison.

Rate Constant (day^{-1})	Notation	Applies to mass in…	Lake Washington	San Francisco Bay [a]	Lake Ontario [b]
Outflow	k_O	Water	0.00117	0.0054	0.00042
Volatilization	k_V	Water	0.00171	0.0044	0.00093
Solids settling	k_{WS1}	Water	0.00656	0.1854	0.0011
Water-to-sediment diffusion	k_{WS2}	Water	0.0000207	0.000035	0.0000082
Degradation in water	k_{WR}	Water	0.000034	0.000034	0.000034
Solids resuspension	k_{SW1}	Sediment	0.0001569	0.001133	0.00014
Sediment-to-water diffusion	k_{SW2}	Sediment	0.0000007	0.0000012	0.000047
Burial	k_B	Sediment	0.0001764	0.0	0.00059
Degradation in sediment	k_{SR}	Sediment	0.000034	0.000034	0.000034

[a] *Davis (2004)*

[b] *Gobas et al. (1995) as cited by Davis (2003)*

The rate constants in Table 1 describe the fractional change in the mass of PCBs in water (or sediment) per day. For example, if the mass of PCBs in the water column on a particular day is 10 kg and the volatilization rate constant is 0.00171 d^{-1}, then 0.0171 kg (10 kg x 0.00171 d^{-1}) will be lost over the day via volatilization from the lake to the atmosphere. Overall, nine rate constants describe the gains and losses of PCBs from the water and sediment. The outflow, volatilization, degradation in water, degradation in sediment, and sediment burial rate constants describe the loss of PCBs from the lake ecosystem. The remaining four rate constants (solids settling, solids resuspension, water-to sediment diffusion, sediment-to-water diffusion) are used to calculate the exchange (gains and losses) between the water column and sediment. The determination of these rate constants is described in more detail below.

A time-varying solution approach[10], using a daily time step, is used to calculate the change in water and sediment PCB concentrations (and mass of PCB in the lake) over time. When the model is run with initial lake water and sediment concentrations of zero and a specified

[10] An explicit first-order Euler method was used as the numerical integration solution.

steady loading rate for a sufficiently long time period, the resulting steady-state water and sediment PCB concentration can be determined. This provides a means of testing the model to determine how well the model matches the observed tPCB lake concentration using the estimated current tPCB loading rate. The same model can also be used to estimate the lake's response to various loading reduction scenarios given the initial steady-state water and sediment concentrations.

4.1 Rate Constants

Although the model is relatively simple, there are 19 input values used to calculate the model rate constants (Table 2). These input values describe the size and characteristics of the water and sediment compartments (physical and chemical). The input values in Table 2 represent the best estimates for each parameter based on site specific data for Lake Washington, or data from the scientific literature that describes the fate of PCBs in aquatic systems.

Because the model currently only simulates the fate of one PCB congener at a time, as in Davis (2004), the chemical properties of PCB-118 (3,3',4,4',5-pentachlorobiphenyl) were used as default values because it has an intermediate level of chlorination and, therefore, intermediate chemical properties. The chemical properties of PCB-118 are also similar to PCB-126, which is the most toxic congener to humans. PCB-118 was detected with some frequency in Lake Washington water samples; however, PCB-126 was not. PCB-126 was also not frequently detected in San Francisco Bay water, but it was the most significant contributor to human and wildlife dioxin-equivalent toxic exposure from bay fish (Davis 2004).

Table 3 identifies four additional model inputs that describe the chemical properties of PCB-118; these values represent the best available information for this congener.

The derivation of the rate constants and the information used to determine the best estimates for the input data are described below.

4.1.1 Losses from the water column

4.1.1.1 Outflow

Outflow: $k_O = F / (1{,}000 * V_W)$ (d^{-1})

The outflow rate constant describes outflow from Lake Washington through the Montlake Cut, which exports dissolved and particulate sorbed PCBs out of Lake Washington to Lake Union. The best outflow rate was based on the long-term (2002-2011) estimate in King County (2013b). The total mass of PCBs lost through outflow was calculated by multiplying k_O by the total mass of PCBs in the water column.

Table 2. Model input data.

Parameter (units)	Symbol	Best Estimate	Source
tPCB load (kg yr^{-1})	L	0.672	King County (2013b)
Water surface area (m^2)	SAW	8.90E+07	Anderson (1954)
Sediment surface area (m^2)	SAS	8.90E+07	Assumed equal to water surface area (SAW)
Active sediment layer depth (m)	DS	0.025	Gobas et al. (1995)
Volume of water (m^3)	VW	2.90E+09	Anderson (1954)
Volume of sediment (m^3)	VoS	2.23E+06	Determined from SAS*DW
Average water temperature (^oC)	TW	10.9	Based on long-term monitoring data
Average wind speed (m s^{-1})	WS	3.3	Based on long-term monitoring data
Water outflow rate (L d^{-1})	F	3.40E+09	King County (2013b)
Suspended particulate matter (kg L^{-1})	CPW	1.0E-06	Based on long-term monitoring data
Sediment solids concentration (kg L^{-1})	CSS	0.12	Based on lake sediment coring data
Water POC concentration (kg L^{-1})	Xpoc	3.0E-7	Based on long-term monitoring data
Water DOC concentration (kg L^{-1})	Xdoc	3.1E-6	Based on long-term monitoring data
Sediment organic carbon content (fraction)	OCSS	0.055	King County (2013d)
Density of sediment organic carbon (kg L^{-1})	dOC	1.0	Gobas et al. (1995), Davis (2004)
Solids settling rate (m d^{-1})	Vs	1.0	Gobas et al. (1995)
Water-to-sediment diffusion coefficient (m d^{-1})	Vd	0.0024	Gobas et al. (1995), Davis (2004)
Sediment burial coefficient (m d^{-1})	Vb	4.41E-06	Wakeham et al. (2004) [a]
Degradation rates in water (d^{-1})	KWR	0.000034	Gobas et al. (1995), Davis (2004)
Degradation rates in sediment (d^{-1})	KSR	0.000034	Gobas et al. (1995), Davis (2004)

[a] Adjusted for sediment focusing.

Table 3. Chemical properties of PCB-118 (3,3',4,4',5-pentachlorobiphenyl).

Property	Symbol	PCB-118[a]	Source
No. of chlorines	--	5	
Molecular formula	--	C12H5Cl5	
$Log_{10}K_{OW}$ @ 25 °C (@ 10.9 °C)	K_{OW}	6.65 (6.86)[b]	Schenker et al. (2005)
Henry's Law constant (Pa m^3 mol^{-1})	H298	10.821	Calculated using equation 6-15 in Schwarzenbach et al. (1993)
Enthalpy of K_{ow} (J/mol)	const_EnthalpyK_{ow}	-24,500	Schenker et al. (2005)
Molar Mass (g mol^{-1})	Mol Wt	326.43	From molecular formula
Molar Volume at Boiling Point (cm^3 mol^{-1})	MVB	289.1	LeBas method (14.8*12+3.7*5+24.6*5-15-15)

[a] PCB-126 has the same chemical formula, so it has the same molar mass and volume as PCB-118. The Henry's Law constant and $Log_{10}K_{OW}$ for PCB-126 are 21.3 Pa m^3 mol^{-1} and 6.60, respectively.

[b] K_{ow} reported at 25 °C was adjusted to a temperature of 10.9 °C using the approach in Pelletier and Mohamedalli (2009) This approach uses the Van't Hoff equation to calculate the change in K_{ow} as a function of temperature and the standard enthalpy of change of the process.

4.1.1.2 Volatilization

Volatilization: $k_V = S_{AW}*FDW*V_E/V_W$ (d^{-1})

where VE is the volatilization mass transfer coefficient,

$1 / V_E = 1 / V_{EW} + 1 / (K_{AW}*V_{EA})$

and V_{EW} and V_{EA} are the water-side and air-side mass transfer coefficients, respectively, and K_{AW} is the temperature-adjusted Henry's Law constant for the modeled PCB congener.

The volatilization rate constant (k_V) describes the transfer of PCBs from their freely dissolved form in water through the surface water interface and into the air. The approach used is based on two-film model theory that is commonly used to estimate PCB loss to the atmosphere across the air-water interface (Chapra 1997). An underlying assumption is that the PCB air concentration is so low, that only transfer from water to air needs to be considered. Consideration of atmospheric absorption would require estimates of PCB concentrations in the air overlying the lake surface (for example see Totten et al. 2001).

The Matlab code for the San Francisco Bay model used as the basis for the Lake Washington model did not include routines to estimate the water-side (V_{EW}) and air-side (V_{EA}) mass transfer coefficients; in that model these variables were determined externally. To provide the capability to estimate these parameters within the model code, the relevant routines described in Johnson (2010) and written in R were adapted for use in the Lake Washington

model. These routines use inputs of average wind speed across the lake surface, average lake water temperature and the chemical characteristics of the modeled PCB (e.g., Henry's Law constant, molar volume, and molar weight) to calculate the volatilization mass transfer coefficient. The long-term (2002-2011) average wind speed of 3.3 m s^{-1} was determined from published hourly observations at nearby Seattle-Tacoma International Airport and the mean water temperature of 10.9 ^{o}C was determined from long-term (2002-2012) volume-weighted averages of temperature profiles (Appendix B) collected from the same three central lake stations sampled during the field study conducted for this project (King County 2013a).

Another modification to the San Francisco Bay model applied here involved calculation of the freely dissolved fraction of PCBs in the water column. This calculation affects determination of the mass of PCBs in the water column that will be affected by volatilization. The San Francisco Bay model considered two-phase partitioning in the water column; partitioning between particulate organic carbon (POC) and the freely dissolved phase (Davis 2004). However, understanding of partitioning of nonionic polar or weakly polar organic chemicals has evolved from consideration of two-phases to three or more phases (Greene et al. 2013). The three-phase model considers partitioning to dissolved organic carbon (DOC) and has been incorporated into fate models of Puget Sound (Pelletier and Mohamedali 2009), the Hudson River (Farley et al. 1999), the Delaware River (Totten et a. 2001, Rowe et al. 2007) and in lake bioaccumulation models (Arnot and Gobas 2004).

The three-phase model in Arnot and Gobas (2004)[11] was incorporated into the Lake Washington model:

$$FDW = 1 / (1 + Xpoc*Dpoc*alpha\_poc*K_{OW} + Xdoc*Ddoc*alpha\_doc*K_{OW})$$

where, Xpoc and Xdoc are the concentrations (in kg/L) of POC and DOC in the water column. Dpoc and Ddoc are the disequilibrium factors for POC and DOC partitioning (unitless). Disequilibrium in partitioning between water and organic matter has been observed in various studies (i.e., hysteresis in the sorption/desorption process), but these values are difficult to determine. Disequilibrium values of 1.0 were used in the model, which represents standard equilibrium partitioning.

The factors alpha_poc and alpha_doc (L/kg_{OC}) relate the estimated partitioning between water and octanol (K_{OW}, unitless) to partitioning to POC and DOC. The values used by Arnot and Gobas (2004) of 0.35 and 0.08 for alpha_poc and alpha_doc, respectively, were selected for use in the Lake Washington model. This implies that for a given input K_{OW} value, the equivalent partitioning to POC and DOC will be somewhat less and that PCB will partition more strongly to POC than DOC.

The average concentrations of water column DOC and POC were based on volume-weighted measurements of DOC and total organic carbon (TOC) made between 2002 and 2008 (DOC and TOC analyses were discontinued after 2008) at the same three central lake stations sampled during the field study conducted for this project. Volume-weighted mean concentrations of TOC and DOC were 3.4 and 3.1 mg/L, respectively (Appendix B). The

[11] This partitioning model is used in the Puget Sound model (Pelletier and Mohamedali 2009).

mean concentration of POC was estimated by the difference between TOC and DOC – equal to 0.3 mg/L.

4.1.1.3 Solids settling

Solids Settling: $k_{WS1} = S_{AW}*V_S*[1 – (FDW + FOW)] / V_W$ (d^{-1})

The parameters that control the solids settling rate constant are the solids settling rate and the fraction of water column PCBs sorbed to settling organic solids. The best estimate of the solids settling rate (Vs) was 1.0 m d^{-1}, which was the value used in the Lake Ontario (Gobas et al. 1995) and San Francisco Bay (Davis 2004) models.

As a result of the incorporation of a three-phase partitioning model, calculation of the fraction of PCB sorbed to settling organic solids requires either the direct determination of the fraction of water column PCB sorbed to POC or the fraction sorbed to DOC. The model uses the latter approach to calculate FOW, the fraction of water column PCB sorbed to DOC:

$$FOW = (Xdoc * Ddoc * alpha\_doc * K_{OW}) / (1 + Xpoc*Dpoc*alpha\_poc*K_{OW} + Xdoc*Ddoc*alpha\_doc*K_{OW})$$

The fraction of PCB in water in the particulate phase is then: 1 – (FDW + FOW).

4.1.1.4 Water-to-sediment diffusion

Water-to-sediment diffusion: $k_{WS2} = S_{AS}*V_D*FDW / V_W$ (d^{-1})

Water-to-sediment diffusion transfers freely dissolved PCBs from the water column to the active sediment layer and is a function of the fraction of freely dissolved PCB (FDW, previously described) and the water-to-sediment diffusion mass transfer coefficient (V_D). The water-to-sediment diffusion mass transfer coefficient used in the model was 0.00024 m d^{-1}, which was the value used in the Lake Ontario (Gobas et al. 1995) and San Francisco Bay (Davis 2004) models. Davis (2004) indicated that the model was relatively insensitive to large (orders of magnitude) changes in this parameter.

4.1.1.5 Degradation in water

Degradation in water: $k_{WR} = 3.4 \times 10^{-5}$ (d^{-1})

This value was also used in the Lake Ontario (Gobas et al. 1995) and San Francisco Bay (Davis 2004) models and corresponds to a half-life of 56 years. This degradation rate is intended to account for all water column degradation pathways, including hydrolysis, photolysis, biodegradation, and reductive dechlorination. The model also assumes that PCBs in dissolved and sorbed phases are subject to the same degradation rate.

4.1.2 Losses from the active sediment layer

4.1.2.1 Burial

Burial: $k_B = S_{AS}*V_B*(1 – FDS) / V_{oS}$ (d^{-1})

The sediment burial rate constant is a function of the surface-area-to-volume ratio of the active sediment layer (S_{AS}/V_{oS}), the particle bound fraction of PCB in sediment (1-FDS) and the sediment burial mass transfer coefficient (V_B).

A two-phase model was used to estimate the fraction of active sediment layer PCBs that would be freely dissolved in the sediment pore water (FDS). The sediment partitioning equation used in the Puget Sound model (Pelletier and Mohamedali 2009) was incorporated into the Lake Washington model:

$$FDS = 1 / OCSS * dOC / (alpha\_poc * K_{OW})$$

Where OCSS is the fraction of sediment organic carbon, dOC is the density of POC ($kg_{OC}\ L^{-1}$). The terms alpha_poc and K_{OW} were introduced above and result in an estimated K_{OC} ($L\ kg_{OC}^{-1}$). The best estimate of the fraction of sediment organic carbon was based on the average concentration of OCSS measured in surface sediments collected from Lake Washington (King County 2013d). The density of organic carbon (dOC) was assumed to be 1.0 kg L^{-1}, which is consistent with the value used for the Lake Ontario model (Gobas et al. 1995).

The sediment burial mass transfer coefficient was based on the sedimentation rate of ~0.25 cm yr^{-1} reported by Wakeham et al. (2004) for a core collected in 2000 from the deeper main basin of the lake. Because sedimentation rates reported for the deepest locations of lakes are likely to be higher than the average sedimentation rate over the entire lake due to sediment focusing – i.e., resuspension and transport from steeper areas along the shoreline and subsequent long-term transport to the deeper and generally flatter areas of the central basin – an adjustment to the reported sedimentation rate was developed following the method outlined in Häkanson and Jansson (2002). The bottom slope (in percent) was calculated from the digital lake bathymetry using the ArcGIS 10.0 Raster Slope Toolbox and the ratio of the lake area with bottom slopes less than 4 percent to the total lake area was calculated. This analysis indicated that 63 percent of the lake bottom had a slope of less than 4 percent. Therefore, the model sediment burial mass transfer coefficient (assuming $S_{AS} = S_{AW}$) was 4.41 x 10^{-6} m d^{-1} (0.25 cm yr-1 ~= 7.0 x 10^{-6} m d^{-1}; 7.0 x 10^{-6} m d^{-1} x 0.63 = 4.41 x 10^{-6} m d^{-1}).

4.1.2.2 Solids resuspension

Solids resuspension: $k_B = (ResFlux / C_{SS})*(1 – FDS) / (1{,}000*V_{oS})\ (d^{-1})$

where $ResFlux = SetFlux – BurFlux$

$SetFlux = 1{,}000*C_{PW}*V_{SS}*S_{AW}$

$BurFlux = 1{,}000*C_{SS}*V_B*S_{AS}$

Sediment solids resuspension transfers PCBs from the active sediment layer to the water column. As in the San Francisco Bay (Davis 2004) and Lake Ontario models (Gobas et al. 1995), the resuspension flux is determined by the difference between the settling solids flux (SetFlux) and the burial flux (BurFlux), which is controlled primarily by the solids settling rate (V_{SS}) and the sediment burial mass transfer coefficient (V_B). Solids resuspension is also dependent on the concentration of sediment solids (CSS) and the total volume of active sediment (VoS). While sediment resuspension was determined to be an

important process in San Francisco Bay, the relatively low resuspension rate constant determined for Lake Washington is more consistent with the one determined for Lake Ontario (Table 1).

The settling flux (SetFlux) is a function of the mean concentration of settling particulate matter in the water column (Cpw), the average particle settling velocity (Vss) and the lake surface area (Saw). The mean concentration of settling particles was determined from the average total suspended solids (TSS) concentration measured between 2002 and 2012 at the same three central lake stations sampled during the field study conducted for this project. The volume-weighted mean concentration of TSS was 1.0 mg/L (Appendix B). The settling rate used in the model was 1.0 m d^{-1}, which was the value used in the Lake Ontario model (Gobas et al. 1995).

4.1.2.3 Sediment-to-water diffusion

Sediment-to-water diffusion: $k_{SW2} = S_{AS}*V_D*FDS / V_{oS}$ (d^{-1})

As with solids resuspension, sediment-to-water diffusion also transfers PCBs from sediment to water. Even though the Lake Washington solids resuspension rate constant is an order of magnitude lower than the constant determined for the San Francisco Bay model (Davis 2004), it is still about three orders of magnitude greater than the sediment-to-water diffusion rate constant (Table 1). The sediment-to-water diffusion rate constant is also lower than the water-to-sediment diffusion rate constant by about two orders of magnitude. These differences are determined mainly by the very low sediment pore water dissolved PCB concentrations and much higher water column dissolved PCB concentrations that are predicted by the sediment and water contaminant partitioning models.

4.1.2.4 Degradation in sediment

Degradation in sediment: $k_{SR} = 3.4 \times 10^{-5}$ (d^{-1})

This value was used in the Lake Ontario (Gobas et al. 1995) and San Francisco Bay (Davis 2004) models and corresponds to a half-life of 56 years. This degradation rate is intended to account for all active sediment degradation pathways, including hydrolysis, biodegradation and reductive dechlorination. The model also assumes that PCBs in dissolved and sorbed phases are subject to the same degradation rate.

4.1.3 Sediment properties

There are fundamentally three important sediment properties that must be specified in the model: depth of active sediment layer, sediment solids concentration and the sediment tPCB concentration. The selection of the best values for these parameters is described below.

4.1.3.1 Depth of active sediment layer

Davis (2004) indicated that the depth of the active sediment layer is one of the most pivotal parameters in the model. This parameter, in conjunction with the area of bottom sediment and sediment solids concentration determines the mass of sediment available for exchange

with the water column. Although the research on San Francisco Bay described by Davis (2004) suggested that the best estimate of the average depth of the active sediment layer was 10 cm (0.010 m), San Francisco Bay is much shallower, and more physically and biologically dynamic, than Lake Washington. Published sediment geochronology studies of Lake Washington indicate very little disturbance of deposited sediments with thin seasonal deposition layers preserved in the sediments (Edmondson and Allison 1970, Edmondson 1975, Edmondson 1991). The logarithmic decline in surface sediment lead-210 profiles and anoxic conditions immediately below the sediment water interface indicate minimal physical or biological disturbance (Wakeham and Carpenter 1976, Furlong 1986). The well-preserved peak in PCB concentrations at depth in the sediment is consistent with peak historical inputs and serves as another indication that sediment disturbance is minimal (Furl et al. 2009, Era-Miller et al. 2010). Visual illustrations of the evidence for limited sediment mixing and a relatively shallow active sediment layer are provided in Figure 4; and suggest that the active sediment layer may be less than 2.5 cm. Based on this information; a depth of 2.5 cm (0.025 m) was selected as the active sediment layer for use in the Lake Washington model. This value is the same as the one used in the Lake Ontario model (Gobas et al. 1995).

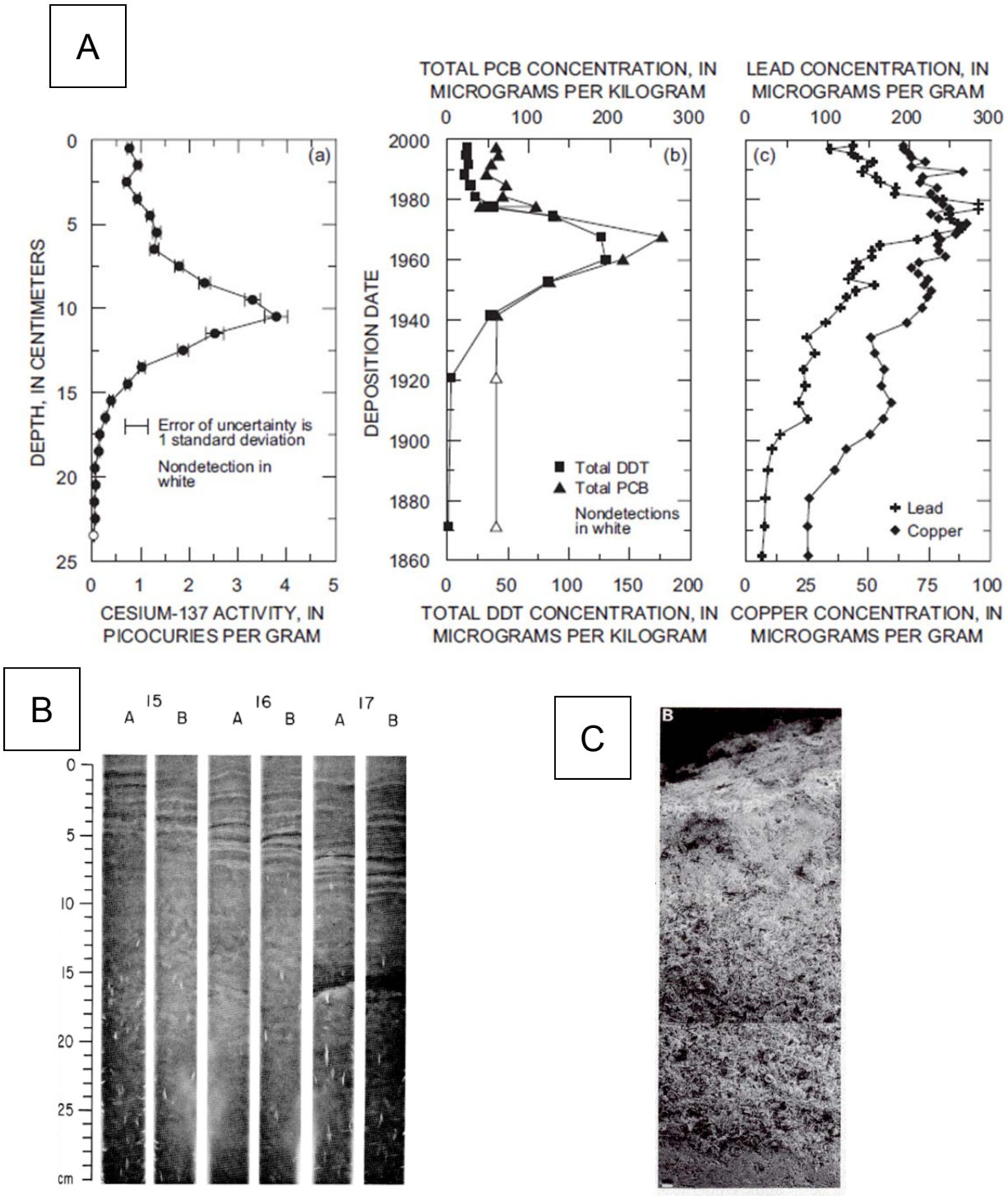

Figure 4. Visual illustrations of limited mixing by physical or biological activity in Lake Washington sediments: A) Cesium-137, DDT, PCB, lead and copper sediment profiles showing preserved contaminant peaks (Van Metre et al. 2004), B) Radiographs showing fine undisturbed sediment layers (Edmondson and Allison 1970), C) Photograph of vertical section of core showing undisturbed sediment layers – small gray bar at bottom is 10 µm (Edmondson 1991).

4.1.3.2 Sediment solids concentration

Sediment investigations that focus on surface contaminants typically include measurement of percent solids (to convert wet sediment analysis results to contaminant concentrations on a dry sediment weight basis), but not measurements of sediment solids concentration. However, sediment geochronology studies involve collection of cores that are typically sectioned and subsampled to determine sediment solids concentration to account for sediment compaction with depth. Fortunately, many sediment cores have been collected and analyzed from Lake Washington over the years as part of various studies conducted by researchers at the University of Washington. Although not all of the sediment solids concentration profiles from these studies have been published, unpublished University of Washington data from 14 cores were made available by Arni Litt (personal communication) for use in this study. Published data include three cores collected by Birch (1976) and six cores collected by Griffiths and Edmondson (1975).

The mean solids concentration in the top 2.5 cm of the 23 sediment cores was 0.12 kg L^{-1}. The median (50^{th} percentile) concentration was 0.11 kg L^{-1} and the 25^{th}- and 75^{th}-percentile concentrations were 0.10 and 0.15 kg L^{-1}, respectively.

4.1.3.3 Average Sediment PCB Concentration

Average tPCB concentrations in the active sediment layer define the mass of tPCB in lake sediments. Because PCBs are generally hydrophobic and sorb strongly to organic solids, the majority of PCBs in lakes and estuaries is stored in sediments and sediment-water interactions lengthen the response time to reductions in PCB loading (Schwarzenbach et al.1993, Gobas et al. 1995, Davis 2004).

Sediment PCB concentration data were available for 69 sampling locations distributed throughout the lake (Table 4) (see King County 2013d for details). The data were obtained from a variety of sampling programs with a range of objectives, some of which focused on characterizing concentrations near suspected contaminant sources. Different objectives and protocols also resulted in different target sampling depths in any particular program. However, the majority of samples represent concentrations in the top 10 cm. Fewer programs targeted the top 2 cm of sediment. The available data are likely biased high due to inclusion of samples from programs specifically attempting to identify nearshore contaminant sources and due to inclusion of data from the top 10 cm of sediment, which likely incorporated higher PCB concentrations that are buried deeper in the sediments (Furl et al. 2009, Era-Miller et al. 2010). In the absence of a spatially stratified random design such as those implemented for characterizing the distribution of San Francisco Bay sediment PCB concentrations (Davis et al. 2007), the available data were used to provide a first approximation of average sediment tPCB concentrations for use in model development and testing.

Concentrations were generally higher along the shallower margins of the lake and lower in deeper offshore areas (Table 4). The spatially-weighted average based on the average tPCB concentrations in shallow (<30 ft) and deeper (>30 ft) lake areas was 55 µg/kg dry sediment.

Table 4. Summary of tPCB concentrations measured in Lake Washington sediments.

Location	Number of Samples	Total PCBs (µg/kg dry)					
		Min	Max	Mean	25th	Median	75th
<30ft depth	41	3.3	577.2	71.2	17.6	29.0	56.5
>30ft depth	28	4.6	184.6	31.8	10.4	15.2	22.5
All locations combined	69	3.3	577.2	55.2	11.4	22.0	53.2

4.1.4 Water properties

Although the water property data selected for input to the model have been documented above, the data are summarized again below. In addition, the water column tPCB data used in model testing are also documented below.

4.1.4.1 Water temperature

The mean water temperature of 10.9°C was determined from long-term (2002-2012) volume-weighted averages of temperature profiles collected from the same three central lake stations sampled during the field study conducted for this project (King County 2013a).

4.1.4.2 Particulate and dissolved organic carbon concentrations

The average concentrations of water column DOC and POC were based on volume-weighted measurements of DOC and TOC made by King County between 2002 and 2008 (DOC and TOC analyses were discontinued after 2008) at the same three central lake stations sampled during the field study conducted for this project. Volume-weighted mean concentrations of TOC and DOC were 3.4 and 3.1 mg/L, respectively (Appendix B). The mean concentration of POC (0.3 mg/L) was estimated by the difference between TOC and DOC.

4.1.4.3 Suspended solids concentrations

The mean concentration of settling particles was determined from the average TSS concentration measured between 2002 and 2012 at the same three central lake stations sampled during the field study conducted for this project. The volume-weighted mean TSS concentration was 1.0 mg/L (Appendix B).

4.1.4.4 Water column tPCB concentration

Lake water tPCB data were collected as part of this study (King County 2013a), which were used to calculate an average water column tPCB value for use in model development and

testing. The tPCB results from the samples integrated from three lake stations (separately from the epilimnion and hypolimnion or from the whole lake depending on whether the lake was well mixed or not) and that were collected every other month for one year (a total of six sampling events) were used to calculate an annual volume-weighted mean tPCB concentration (Table).[12] The calculated annual mean volume-weighted tPCB concentration was 92 pg/L.

Table 5. Summary of measured water column tPCB concentrations (pg/L).

Statistic	tPCB (pg/L)
Volume-weighted mean	92
25th-percentile	51
Median (50th-percentile)	61
75th-percentile	118

4.1.5 External tPCB load

The external tPCB load to the lake, including inputs from rivers, streams, bridge runoff and the atmosphere based on data collected as part of this study is documented in King County (2013b). The best estimate of tPCB loading to the lake was 0.672 kg yr-1. Upper and lower estimates were also provided for the various sources, which allow calculation of a range that brackets the best estimate. These estimates range from 0.333 to 0.889 kg yr^{-1}. These loading estimates provide an indication of the uncertainty in tPCB loading and input data with which to test the effect of uncertainty in tPCB loading on fate (and bioaccumulation model) predictions.

4.1.6 Export of tPCB through the lake outlet

The amount of tPCB exported from Lake Washington via the lake outlet was also determined based on measured outlet tPCB concentrations and a lake water budget documented in King County (2013b). The estimated average tPCB export was 0.140 kg yr^{-1}. This estimate can be compared to the fate model prediction to test the ability of the model to estimate the magnitude of loss via this pathway. A reasonable match between observed water and sediment concentrations and loss through the outlet would suggest a reasonably good prediction of the loss via volatilization from the surface of the lake.

[12] See King County (2013a) for details regarding sample integration methods and tPCB concentration data.

5.0 BIOACCUMULATION MODEL INPUT DATA

The bioaccumulation model mathematically represents the balance between PCB uptake from ingestion and respiration and elimination from respiration, egestion, metabolism, and growth dilution in a linear and steady state relationship. As a single algorithm, the model can be viewed as the following for invertebrates and fishes (Condon 2007):

$$C_{Bj} = \frac{\{k_{1j} * (m_O * \varphi * C_{WT,O} + m_P * C_{WD,S,j}) + k_{Dj} * \Sigma P_i * C_{D,J,i}\}}{(k_{2j} + k_{Ej} + k_{Gj} + k_{Mj})} \quad (3)$$

Where:

C_{Bj} = concentration of congener j in organism (ng/g wet weight)

k_{1j} = rate of congener uptake from respiration (d^{-1})

m_O = fraction of respiratory ventilation that involves overlying water (unitless)

φ = fraction of congener in overlying water that can be absorbed (unitless)

$C_{WT,O}$ = total concentration of congener j in overlying water (ng/mL)

m_p = fraction of respiratory ventilation that involves pore water (unitless)

$C_{WD,S,j}$ = freely dissolved concentration of congener j in pore water (ng/mL)

k_{Dj} = rate of congener j uptake by dietary ingestion (d^{-1})

P_i = fraction of diet consisting of prey item I (unitless)

$C_{D,J,I}$ = concentration of congener j in prey item I (g/kg)

k_{2j} = rate of congener j elimination from respiration (d^{-1})

k_{Ej} = rate of congener j elimination from egestion (d^{-1})

k_{Gj} = rate of congener j elimination from growth (d^{-1})

k_{Mj} = rate of congener j elimination from metabolic transformation (d^{-1})

The balance of PCB uptake and elimination is modeled more simply for phytoplankton because ingestion, egestion and metabolic transformation are assumed to be zero. This simplified model algorithm is:

$$C_{Bj} = \frac{(k_{1j} * C_{WD,S,j})}{(k_{2j} + k_{Gj})} \quad (4)$$

See above for definition of terms.

The terms in equations 3 and 4 are calculated using the same submodels presented in Condon (2007) which will not be repeated here. The changes required to adapt the model for use in Lake Washington were:

- Salinity for freshwater was assumed to be 0 ppt.
- The submodels for birds and mammals were not used.
- Lake Washington-specific parameter values were used when available.

The rest of this section summarizes the input values assumed for lake, PCB chemistry, biology, and dietary parameters as well as the conceptual food web for Lake Washington. Input values were estimated to represent average conditions in Lake Washington.

5.1 Lake Parameters

A number of parameter values representing lake conditions were estimated using published and unpublished empirical data from Lake Washington (Table 6). The mean annual water temperature and mean concentrations of suspended solids, DOC, POC and dissolved oxygen were estimated as a volume-weighted average value of measurements between 2002-2012 from three King County long-term monitoring stations. Where applicable, these values are the same as those used in the fate model (Section 4.1.4). A mean POC concentration was calculated by subtracting the volume-weighted mean DOC concentration from the volume-weighted mean TOC concentration. The sediment organic carbon content parameter was estimated based on the mean of available sediment data collected by King County and Ecology (King County 2013d). This is the same value that was used in the fate model.

The remaining lake parameters (e.g., density of organic carbon in sediment, disequilibrium factors, proportionality constants) could not be estimated from any Lake Washington-specific empirical data. Thus, these parameters were estimated based on values used by others who have modeled bioaccumulation of PCBs in San Francisco Bay and Puget Sound.

Table 6. Bioaccumulation model parameter values

Model parameter	Symbol	Mean	Source
Concentration of particulate organic carbon in water (kg/L)	*Xpoc*	3.00E-07	Calculated from volume-weighted average TOC and DOC
Concentration of dissolved organic carbon in water (kg/L)	*Xdoc*	3.09E-06	Volume-weighted average from three Lake WA stations 2002-2008
Concentration of suspended solids (kg/L)	Vss	1.01E-06	Volume-weighted average from three Lake WA stations 2002-2012
Mean annual water temperature (^{o}C)	Tw	10.9	Volume-weighted average from three Lake WA stations 2002-2012
Salinity (g/kg)	PSU	0	Assumed
Density of organic carbon in sediment (kg/L)	d_{OCS}	1	Gobas et al. (1995), Davis (2004)
Organic carbon content of sediment (unitless)	OCS	0.055	Mean sediment concentration based on available King County and Ecology sediment data (King County 2013d)
Dissolved oxygen concentration @ 90% saturation (mg O_2/L)	Cox	9.29	Volume-weighted average from three Lake WA stations 2002-2012 and adjusted to 90% saturation
Absolute temperature (K)	Tabs	273.16	Known constant
Molar concentration of seawater @ 35 ppt (mol/L)	MCS	0	Assumed
Disequilibrium factor for POC partitioning in water column (unitless)	Dpoc	1	Default values from Arnot and Gobas 2004 (eqn 4)
Disequilibrium factor for DOC partitioning in water column (unitless)	Ddoc	1	Default values from Arnot and Gobas 2004 (eqn 4)
Proportionality constant for phase partitioning of POC (unitless)	alphaPOC	0.35	Default values from Arnot and Gobas 2004 (eqn 4)
Proportionality constant for phase partitioning of DOC (unitless)	alphaDOC	0.08	Default values from Arnot and Gobas 2004 (eqn 4)

5.2 PCB Chemistry Parameters

The chemistry parameters necessary for the bioaccumulation model are the log K_{ow}, molecular weight, and LeBas molar volume (Table Table 7). The same values used for PCB-118 in the fate model were assumed for the bioaccumulation model parameters.

Table 7. Chemistry parameters for PCB-118

Model Parameter	Symbol	PCB-118[a]	Source
$Log_{10}K_{OW}$ @ 10.9°C	KOW	6.86	Schenker et al. (2005)
Molar Mass (g mol^{-1})	MolWt	326.43	From molecular formula
Molar Volume at Boiling Point (cm^3 mol^{-1})	MVB	289.1	LeBas method (14.8*12+3.7*5+24.6*5-15-15)

5.3 Food Web Structure and Dietary Assumptions

Certain fish species were initially identified for bioaccumulation modeling due to their inclusion in the Washington State fish consumption advisory for PCBs (WADOH 2004): northern pikeminnow (*Ptychocheilus oregonensis*), cutthroat trout (*Oncorhynchus clarkii*) and yellow perch (*Perca flavescens*). Other fish species were added based on their importance as prey items or top predators. Some fish species known to reside in Lake Washington, such as brown bullhead (*Ameiurus nebulosus*) and common carp[13] (*Cyprinus carpio*), were not included in the food web model because they are not key prey items for other fish, and limited information (e.g., diet composition, whole body PCB tissue concentrations) was available from published Lake Washington studies to enable bioaccumulation modeling. Adult salmon species were not included in the model because these migratory fish spend most of their life cycle in the ocean, only passing through Lake Washington to reach upstream spawning areas, and thus, their tissue concentrations are not reflective of PCB exposure in Lake Washington. Adult salmon are also top predators and, therefore, not prey items necessary to model other species. Juvenile sockeye (*Oncorhynchus nerka*) was selected for modeling because young sockeye reside a year or more in Lake Washington before migrating to the ocean (WDFW 2013); they are also an important prey item for several piscivorous species of interest. Invertebrates were selected for modeling based on their identification as prey items for modeled fish species in published diet studies. The taxa selected for the bioaccumulation model are presented in Figure 5. Modeled fish species include juvenile sockeye salmon, longfin smelt (*Spirinchus thaleichthys*), peamouth chub (*Mylcheilus caurinus*), large and small yellow perch,

[13] Common carp are included in the WADOH fish consumption advisory; however, the advisory was based on fillet-only concentrations. Previous studies of the Lake Washington food web have not included common carp. Modeling of the three other species in the advisory is considered to be adequate to provide information to advise future management decisions which would also benefit carp.

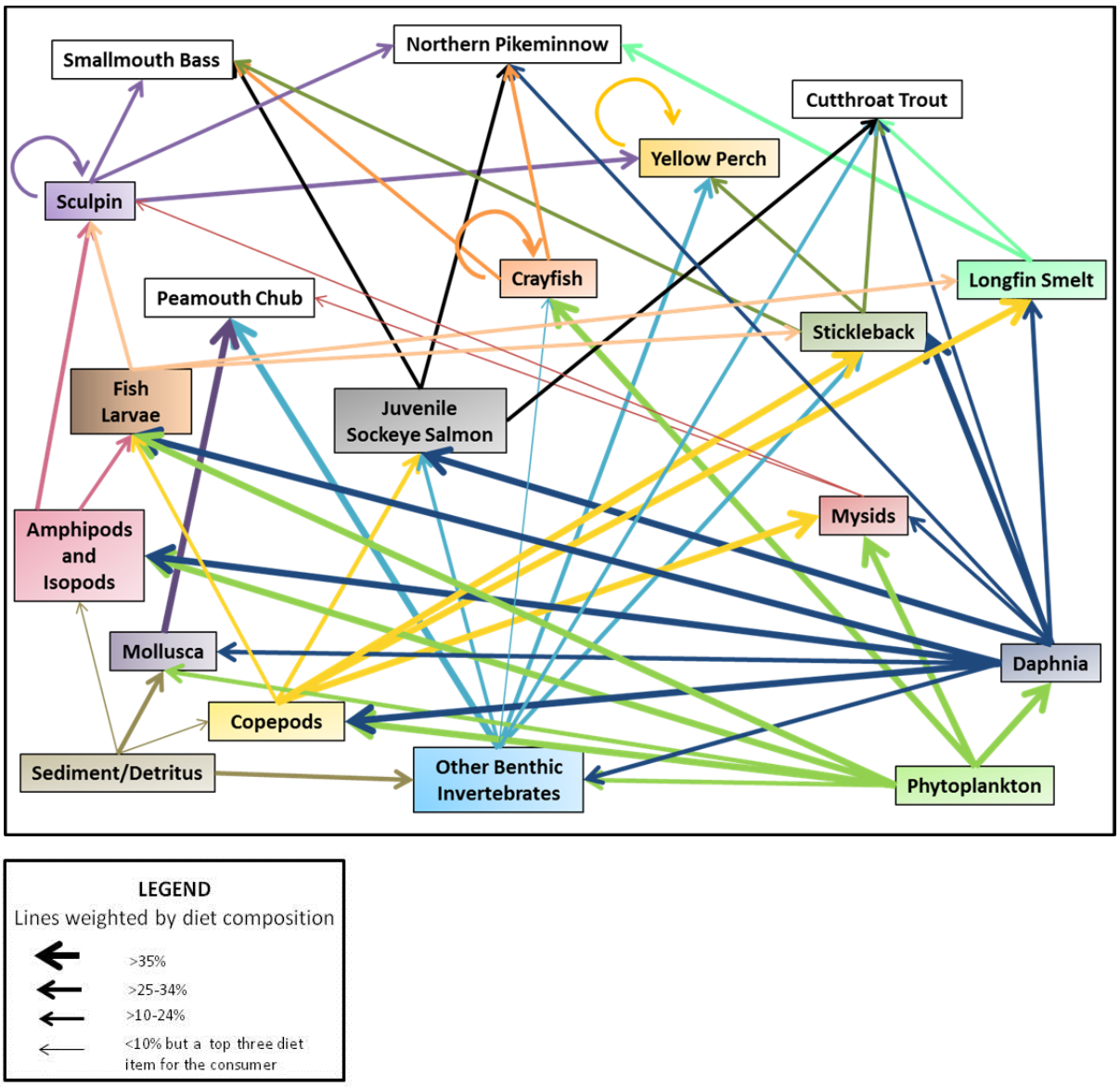

Figure 5. Detailed conceptual food web for Lake Washington

threespine stickleback (*Gasterosteus aculeatus*), prickly sculpin (*Cottus asper*), smallmouth bass (*Micropterus dolomieu*), cutthroat trout and northern pikeminnow. Modeled invertebrate taxa include copepods, amphipods/isopods[14], mollusks, other benthic

[14] This group is modeled based on amphipods but also represents small fractions of isopods identified in the prickly sculpin diet.

invertebrates[15], daphnia species, mysids (*Neomysis mercedis*), and small and large signal crayfish (*Pacifastacus leniusculus*).

The fractions of prey items assumed for the bioaccumulation model were defined using published dietary studies from Lake Washington, where possible, and otherwise, using published studies from other areas. Fractions of prey items from diet studies sampling over multiple seasons were averaged across seasons to calculate an annual mean fraction. Diets of all fish species were defined based on dietary studies of Lake Washington fish (Table 8). Dietary information for two species of fish, yellow perch and prickly sculpin, indicated they were cannibalistic, eating other, presumably smaller, members of their species. To account for this cannibalism, a smaller cohort of this species was added to the food web to serve as a dietary item for the large cohort. To prevent the model from generating a negative tissue concentration, this smaller cohort was assumed to not be cannibalistic. Cannibalism also occurs in signal crayfish; thus, a small and large cohort was also modeled for this species.

An adjustment was made to the published threespine stickleback diet (McIntyre 2004) based on the stable isotope study results of McIntyre (2004). McIntyre (2004) found that the high nitrogen isotope signature of threespine stickleback indicated they fed high on the food web, similar to longfin smelt and piscivores. However, stomach content data from the same study (McIntyre 2004) showed consumption of only cladocera, copepods and a small amount of benthic invertebrates. Other threespine stickleback studies have shown that this species feeds substantially on fish eggs and fry (Bigelow and Schroeder 2002, Lavin and McPhail 2011). The McIntyre (2004) stable isotope study also found a similarly high nitrogen isotope signature for longfin smelt which consume zooplankton and benthic invertebrates, but were also found to have an average across seasons of 20% fish larvae (by mass) in their stomach. Consumption of fish larvae would raise the nitrogen isotope signature in fish that are otherwise planktivores. The sample size of threespine stickleback was relatively small at 35 individuals. Also, depending on the habitat these individuals were collected from within Lake Washington, they may have consumed different diets than the fish sampled for PCB analysis; threespine stickleback physical jaw structure and diet can vary by habitat zone within the same water body (Lavin and McPhail 2011). For all the reasons mentioned, the diet for threespine stickleback was adjusted to reflect the same proportion of fish larvae as longfin smelt (20%).

Modeling bioaccumulation of PCBs in fish larvae presents challenges in defining parameters for diet, lipid composition, wet weight, etc. for an organism that in the egg stage does not eat prey, has an unknown tissue concentration of PCBs transferred from the mother, and is an unidentified species in diet studies. It is expected that the lipid content of fish larvae is higher than mature fish of the same species and that, with maternal transfer, tissue concentrations are higher than primary consumers (i.e., herbivorous zooplankton).

As an alternative to making estimations for all the model parameters needed to predict tissue concentrations in fish larvae, the fractions of fish larvae for the three modeled fish species that consume them (longfin smelt, prickly sculpin, and threespine stickleback)

[15] If prey items were identified in diet studies as "benthos" or "benthic invertebrates", they were assigned to this modeled taxon. Chironomids are included in this taxonomic group.

were modeled as sediment. The mean PCB concentration in sediment measured in Lake Washington and used in the bioaccumulation model is 55 µg/kg (dry weight) and is lower than tissue concentrations predicted for benthic invertebrates and crayfish. Thus, this assumption may potentially underestimate exposure from fish larvae, but results in a higher exposure than assuming consumption of phytoplankton, daphnids, and copepods.

Table 8. Diet fraction assumptions for modeled taxa

Prey → / Consumer ↓	Sediment	Phytoplankton	Daphnia	Mysids	Copepods	Amphipods and Isopods	Mollusca	Crayfish Small	Crayfish Large	Other Benthic Invertebrates	Sockeye Salmon (juvenile)	Longfin Smelt	Threespine Stickleback	Peamouth Chub	Prickly Sculpin Small	Prickly Sculpin Large	Yellow Perch Small	Yellow Perch Large	Smallmouth Bass	Cutthroat Trout	Northern Pikeminnow	Source	Sample Number
Daphnia		1.00																				Winder & Schindler (2004)	—
Mysids	0.05	0.35	0.24		0.36																	Siegbried & Kopache (1980)[a]	—
Copepods	0.05	0.50	0.45																			Estimated	—
Amphipods and Isopods	0.05	0.50	0.45																			Morrison et al. (1997)[b]	—
Mollusca	0.34	0.33	0.33																			EPA (2009b)	—
Crayfish Large		0.75						0.13		0.06	0.01	0.01	0.01	0.01		0.01		0.01				Agric (1995)	712[d]
Crayfish Small	0.02	0.77								0.21												Agric (1995)	712[d]
Other Benthic Invertebrates	0.34	0.33	0.33																			EPA (2009b)	—
Sockeye Salmon (juvenile)			0.53	0.04	0.33					0.10												McIntyre (2004)	55
Longfin Smelt	0.20[d]		0.30	0.06	0.35					0.09												McIntyre (2004)	61
Threespine Stickleback	0.20[d]		0.35		0.35					0.10												McIntyre (2004)[a]	35
Peamouth Chub		0.04	0.04	0.08		0.06	0.38			0.40												Shanbhogue (1976)[c]	485
Prickly Sculpin Large	0.13[d]			0.10		0.31	0.01		0.04	0.09	0.08		0.04		0.16		0.04					Tabor et al. (2004 and 2007)	4198
Prickly Sculpin Small				0.16		0.07	0.04		0.02	0.66	0.01		0.02				0.02					Tabor et al. (2004 and 2007)	111
Yellow Perch Large			0.04	0.04						0.29	0.09	0.09	0.10			0.25	0.10					McIntyre (2004)	32
Yellow Perch Small			0.24	0.38						0.25	0.04	0.04	0.05									McIntyre (2004)	168

Prey → / Consumer ↓	Sediment / Detritus	Phytoplankton	Daphnia	Mysids	Copepods	Amphipods and Isopods	Mollusca	Crayfish Small	Crayfish Large	Other Benthic Invertebrates	Sockeye Salmon (juvenile)	Longfin Smelt	Threespine Stickleback	Peamouth Chub	Prickly Sculpin Small	Prickly Sculpin Large	Yellow Perch Small	Yellow Perch Large	Smallmouth Bass	Cutthroat Trout	Northern Pikeminnow	**Source**	**Sample Number**
Smallmouth Bass			0.05		0.05				0.20	0.03	0.13	0.05	0.20	0.05		0.20	0.00	0.05				Fayram and Sibley (2000)	50
Cutthroat Trout			0.13	0.05						0.24	0.13	0.23	0.17			0.03		0.02				Mazur (2004)	200
Northern Pikeminnow			0.13				0.02		0.11	0.05	0.16	0.32	0.04			0.10		0.07				Brocksmith (1999)	123

Fractions are estimates of average percent composition of diet by wet weight except where noted.

[a] Adapted

[b] Based on Gammarus diet

[c] Based on percent volume

[d] Represents fish eggs/larvae

For invertebrate taxa except daphnids, dietary studies from Lake Washington could not be identified. Diet composition for large and small signal crayfish, and mysids were defined directly from dietary studies outside this region (Agric 1995, Siegbried and Kopache 1980). Diet compositions for copepods, amphipods/isopods, mollusks, and benthic invertebrates were derived from assumptions used in other bioaccumulation models (Morrison et al. 1999, EPA 2009b). These models based their assumptions for benthic invertebrates on Covich et al. (1999) stating that these species are a mix of herbivores, detritivores, and carnivores and therefore, can be modeled by splitting their diet evenly between sediment, phytoplankton and zooplankton. This approach was also assumed for mollusks and benthic invertebrates in this bioaccumulation model. However, the diets of copepods and amphipods/isopods were modified from this basic assumption because their feeding strategies are diverse, but do not include direct sediment ingestion. Harpacticoid copepods, amphipods and isopods feed on the surface of the bottom sediments. Harpacticoid copepods are scrapers, removing food from plant and sediment particles, and amphipods include omnivores, scavengers and detritivores that consume bacteria, algae, and animal and plant detritus (Wetzel 1975, Pennak 1989) although the animal detritus may be coarse particles or freshly killed organisms (Pennak 1989, Voshell 2003). The other two types of copepods, calanoid and cyclopoid, feed by filtration or opportunistic raptorial behavior and are herbivorous or carnivorous (Wetzel 1975). Thus, some species of copepods, amphipods and isopods may ingest some sediment, if only incidentally, but their rate of sediment ingestion is expected to be lower than mollusks and benthic invertebrates living within the sediments. Agric (1995) measured sediment fractions in signal crayfish guts at about 0% for larger (20-45 mm) and 2% for smaller (<20 mm) individuals. Signal crayfish also feed along the surface of the sediments on plant and animal matter. The sediment fraction for copepods and amphipods/isopods was assumed to be 5%, slightly higher than crayfish. The remainder of the diet was split between phytoplankton (50%) and zooplankton (45% daphnia) to represent the algae and animal matter consumed.

5.4 Biological Parameters

Values for biological parameters used in the bioaccumulation model were derived from either empirical data specific to Lake Washington, where possible, or the general literature or were estimated. Some of the biological parameters are specific to each modeled taxonomic group or taxon but many are general, applying across multiple modeled taxa. Table 9 presents values for general biological parameters which include the non-lipid organic matter – octanol proportionality constant, the particle scavenging efficiency of filter-feeders, growth rate factors, fractions of respiration involving pore water, dietary assimilation efficiencies, dietary chemical transfer efficiencies (EdA and EdB), diffusive transfer efficiency (EwA) and metabolic transformation rate.

Table 9. General biological parameters

Organisms	Model parameter	Symbol	Mean	Source
All	Non-lipid organic matter – octanol proportionality constant (unitless)	β	0.035	Gobas et al. 1999
Filter-feeding Invertebrates	Particle scavenging efficiency	σ	1	Default value
Fish	Growth rate factor (unitless)	GRF_F	0.0007	Gobas and Arnot 2005
Invertebrates	Growth rate factor (unitless)	GRF_I	0.00035	Gobas and Arnot 2005
Pelagic zooplankton	Fraction of respiration that involves sediment pore water	mP	0	Estimated
Mysids, Amphipods and Isopods	Fraction of respiration that involves sediment pore water	mP	0.01	Estimated
Mollusks and Crayfish	Fraction of respiration that involves sediment pore water	mP	0.05	Estimated
Benthic Invertebrates	Fraction of respiration that involves sediment pore water	mP	0.10	Estimated
Fish	Fraction of respiration that involves sediment pore water	mP	0	Estimated
Zooplankton	Dietary absorption efficiency of lipid	ε_L	0.72	Arnot and Gobas 2004
Zooplankton	Dietary absorption efficiency of NLOM	ε_N	0.72	Arnot and Gobas 2004
Invertebrates	Dietary absorption efficiency of lipid	ε_L	0.75	Arnot and Gobas 2004
Invertebrates	Dietary absorption efficiency of NLOM	ε_N	0.75	Arnot and Gobas 2004
Fish	Dietary absorption efficiency of lipid	ε_L	0.92	Arnot and Gobas 2004
Fish	Dietary absorption efficiency of NLOM	ε_N	0.6	Arnot and Gobas 2004
Invertebrates and Fish	Dietary absorption efficiency of water	ε_W	0.25	Arnot and Gobas 2004
Invertebrates and Fish	ED constant A	EdA	8.50E-08	Gobas and Arnot 2005
Invertebrates and Fish	ED constant B	EdB	2.0	Gobas and Arnot 2005
Poikilotherms/Homeotherms	Metabolic transformation rate (d^{-1})	k_{Mp}	0	Arnot and Gobas 2004
Poikilotherms	Ew constant A (unitless)	E_WA	1.85	Arnot and Gobas 2004

Notes: NLOM – non-lipid organic matter

Taxon-specific biological parameter values used in the bioaccumulation model are presented for each modeled taxon in Tables 10-29. The biological parameters specific to phytoplankton were based on published literature values used in other bioaccumulation models such as EPA's KABAM model for pesticide bioaccumulation in freshwater systems (EPA 2009b) or general Gobas-type models for bioaccumulation of hydrophobic organic chemicals (Arnot and Gobas 2004, Gobas and Arnot 2005) (Table 10). Biological parameter values for many of the individual modeled taxa were based on empirical data from Lake Washington. Empirical data from Lake Washington were available for body weights, lipid fractions, and water fractions for all the modeled fish species and for some of the modeled invertebrate taxa. The two studies from which these empirical data were obtained were McIntyre (2004) and King County (2013e). However, unpublished raw data was also obtained from the McIntyre (2004) author, J. McIntyre, to enable calculation of mean values for biological parameters. Most of these unpublished data were summarized in King County (2013e). However, the tissue solids data used to calculate mean values for the water fraction parameter were not included in McIntyre (2004) or King County (2013e). The percent solids data from J. McIntyre used to calculate mean water fractions are presented in Appendix A. Non-lipid organic matter fractions were derived (Labeled as "Deduced" in tables) by subtraction of the lipid and water fractions from a total of 1.0. The Yes/No parameter for filter feeders was set based on the dominant feeding mechanism for the species in the taxon.

Table 10. Phytoplankton biological parameters

Model parameter	Symbol	Units	Mean	Source
Lipid fraction in plant	v_{LB}	Unitless	0.012	Derived from EPA 2009b
Non-lipid organic carbon fraction in plant	v_{NB}	Unitless	0.088	Deduced
Water fraction in plant	v_{WB}	Unitless	0.90	EPA 2009b
Growth rate constant	k_G	d^{-1}	0.125	Gobas and Arnot 2005
Aqueous phase resistance constant	A_P	Unitless	6.00E-05	Arnot and Gobas 2004
Organic phase resistance constant	B_P	Unitless	5.50E+00	Arnot and Gobas 2004

Table 11. Daphnia biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	1.0E-07	Peters and Downing 1984
Lipid fraction in biota (unitless)	vLB	Unitless	0.02	McIntyre unpublished
Filter feeders "Yes" or "No"	filterFeeder	Unitless	Yes	Estimated
Non-lipid organic matter fraction in biota	vNB	Unitless	0.06	Deduced
Water fraction in biota	vWB	Unitless	0.92	McIntyre (Appendix A)

Table 12. Mysid biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	1.2E-05	Morrison et al. 1999
Lipid fraction in biota (unitless)	vLB	Unitless	0.05	Oliver and Niimi 1988; Morrison et al. 1999
Filter feeders “Yes" or "No"	filterFeeder	Unitless	Yes	Estimated
Non-lipid organic matter fraction in biota	vNB	Unitless	0.10	Deduced
Water fraction in biota	vWB	Unitless	0.85	McIntyre (Appendix A)

Table 13. Copepod biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	5.7E-08	Peters and Downing 1984
Lipid fraction in biota (unitless)	vLB	Unitless	0.01	McIntyre unpublished
Filter feeders “Yes" or "No"	filterFeeder	Unitless	Yes	Estimated
Non-lipid organic matter fraction in biota	vNB	Unitless	0.10	Deduced
Water fraction in biota	vWB	Unitless	0.89	McIntyre (Appendix A)

Table 14. Amphipod and Isopod biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	7.5E-06	Peters and Downing 1984
Lipid fraction in biota (unitless)	vLB	Unitless	0.01	McIntyre 2004
Filter feeders “Yes" or "No"	filterFeeder	Unitless	No	Estimated
Non-lipid organic matter fraction in biota	vNB	Unitless	0.10	Deduced
Water fraction in biota	vWB	Unitless	0.89	McIntyre (Appendix A)

Table 15. Benthic Invertebrates biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	9.3E-06	Lobo and Alves 2011
Lipid fraction in biota (unitless)	vLB	Unitless	0.03	EPA 2009b
Filter feeders “Yes" or "No"	filterFeeder	Unitless	No	Estimated
Non-lipid organic matter fraction in biota	vNB	Unitless	0.28	Deduced
Water fraction in biota	vWB	Unitless	0.69	McIntyre (Appendix A)

Table 16. Mollusks biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.002	EPA 2009b
Lipid fraction in biota (unitless)	vLB	Unitless	0.03	Morrison et al. 1999
Filter feeders “Yes" or "No"	filterFeeder	Unitless	Yes	Estimated
Non-lipid organic matter fraction in biota	vNB	Unitless	0.18	Deduced
Water fraction in biota	vWB	Unitless	0.80	Estimated

Table 17. Crayfish Large (>90 mm TL) biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.0372	King County 2013e
Lipid fraction in biota (unitless)	vLB	Unitless	0.01	McIntyre unpublished
Filter feeders “Yes" or "No"	filterFeeder	Unitless	No	Estimated
Non-lipid organic matter fraction in biota	vNB	Unitless	0.24	Deduced
Water fraction in biota	vWB	Unitless	0.75	McIntyre (Appendix A)

Table 18. Crayfish Small (<90 mm TL) biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.00046	McIntyre 2004
Lipid fraction in biota (unitless)	vLB	Unitless	0.01	Assumed same as large crayfish
Filter feeders “Yes" or "No"	filterFeeder	Unitless	No	Estimated
Non-lipid organic matter fraction in biota	vNB	Unitless	0.24	Deduced
Water fraction in biota	vWB	Unitless	0.75	Assumed same as large crayfish

Table 19. Juvenile Sockeye Salmon biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.0142	King County 2013e
Lipid fraction in biota (unitless)	vLB	Unitless	0.05	King County 2013e
Non-lipid organic matter fraction in biota	vNB	Unitless	0.21	Deduced
Water fraction in biota	vWB	Unitless	0.74	McIntyre (Appendix A)

Table 20. Longfin smelt biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.00533	King County 2013e
Lipid fraction in biota (unitless)	vLB	Unitless	0.06	King County 2013e
Non-lipid organic matter fraction in biota	vNB	Unitless	0.18	Deduced
Water fraction in biota	vWB	Unitless	0.76	McIntyre (Appendix A)

Table 21. Peamouth chub biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.295	King County 2013e
Lipid fraction in biota (unitless)	vLB	Unitless	0.11	King County 2013e
Non-lipid organic matter fraction in biota	vNB	Unitless	0.19	Deduced
Water fraction in biota	vWB	Unitless	0.70	King County (Appendix A)

Table 22. Prickly sculpin large (>74 mm TL) biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.0221	McIntyre unpublished
Lipid fraction in biota (unitless)	vLB	Unitless	0.02	King County 2013e
Non-lipid organic matter fraction in biota	vNB	Unitless	0.19	Deduced
Water fraction in biota	vWB	Unitless	0.79	McIntyre (Appendix A)

Table 23. Prickly sculpin small (<75 mm TL) biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.00033	King County 2013e
Lipid fraction in biota (unitless)	vLB	Unitless	0.025	King County 2013e
Non-lipid organic matter fraction in biota	vNB	Unitless	0.18	Deduced
Water fraction in biota	vWB	Unitless	0.80	King County and McIntyre (Appendix A)

Table 24. Yellow perch large (>224 mm FL) biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.296	King County 2013e
Lipid fraction in biota (unitless)	vLB	Unitless	0.05	King County 2013e
Non-lipid organic matter fraction in biota	vNB	Unitless	0.25	Deduced
Water fraction in biota	vWB	Unitless	0.70	McIntyre (Appendix A)

Table 25. Yellow perch small (<225 mm FL) biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.047	King County 2013e
Lipid fraction in biota (unitless)	vLB	Unitless	0.02	King County 2013e
Non-lipid organic matter fraction in biota	vNB	Unitless	0.21	Deduced
Water fraction in biota	vWB	Unitless	0.77	McIntyre (Appendix A)

Table 26. Threespine stickleback biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.00375	King County 2013e
Lipid fraction in biota (unitless)	vLB	Unitless	0.06	King County 2013e
Non-lipid organic matter fraction in biota	vNB	Unitless	0.24	Deduced
Water fraction in biota	vWB	Unitless	0.70	McIntyre (Appendix A)

Table 27. Smallmouth bass biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.755	King County 2013e
Lipid fraction in biota (unitless)	vLB	Unitless	0.05	King County 2013e
Non-lipid organic matter fraction in biota	vNB	Unitless	0.25	Deduced
Water fraction in biota	vWB	Unitless	0.70	King County and McIntyre (Appendix A)

Table 28. Cutthroat trout biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.530	King County 2013e
Lipid fraction in biota (unitless)	vLB	Unitless	0.04	King County 2013e
Non-lipid organic matter fraction in biota	vNB	Unitless	0.24	Deduced
Water fraction in biota	vWB	Unitless	0.72	McIntyre (Appendix A)

Table 29. Northern pikeminnow biological parameters

Model parameter	Symbol	Unit	Value	Source
Wet weight of the organism (kg)	WB	kg	0.493	King County 2013e
Lipid fraction in biota (unitless)	vLB	Unitless	0.06	King County 2013e
Non-lipid organic matter fraction in biota	vNB	Unitless	0.22	Deduced
Water fraction in biota	vWB	Unitless	0.72	King County and McIntyre (Appendix A)

6.0 SENSITIVITY AND UNCERTAINTY ANALYSIS APPROACH

The approach taken to evaluate model sensitivity and uncertainty of the fate and bioaccumulation models described previously is described below.

6.1 Sensitivity

To evaluate model sensitivity, parameters were assigned to lognormal distributions with a standard deviation of 5% and sampled by Monte Carlo for 1000 simulations. Then, a Spearman rank order correlation analysis between parameter values and model output was conducted to determine the percent contribution to variance. These steps were automated using a Microsoft Excel Add-In called YASAIw provided as freeware by Ecology (Pelletier 2009). YASAIw is a modified version of YASAI (Yet Another Simulation Add-In for Excel) developed by Eckstein et al. (2000) to facilitate sensitivity and Monte Carlo analysis of models. This report describes the degree of relative influence of each parameter on model results in Section 7.0. This report also describes the degree of relative influence of the tested parameters and discusses implications for the interpretation of results.

All of the input parameters that were not considered to be known with a great deal accuracy (e.g., the volume of the lake was considered to be known with a high degree of accuracy, but the average wind speed was not) were included in the fate model sensitivity analysis. For the bioaccumulation model, the abiotic and biological parameter values, LeBas molar volume, molecular weight, and site-specific PCB concentrations in water and sediment were included in the sensitivity analysis. Log K_{ow} (octanol-water partitioning coefficient) was not included because others have documented that Gobas-type bioaccumulation models are very sensitive to log K_{ow} (EPA 2009b). Log K_{ow} has previously been shown to have the greatest influence (over 70% overall contribution to variance) of any parameter on the model output (EPA 2009b). This is congruent with the fact that log K_{ow} is integral to several partitioning algorithms used in the model (Arnot and Gobas 2004). Thus, exclusion of log K_{ow} from the sensitivity analysis allows for closer examination of the sensitivity[16] of the other input parameters.

The food web structure and feeding preferences in the bioaccumulation model influence predicted tissue concentrations, but present challenges to testing by the same sensitivity analysis tool used for the other parameters (e.g., diet fractions are linked and the species of modeled prey items may vary) and are not typically tested. Conducting sensitivity analysis of the food web structure and dietary assumptions was considered beyond the scope of this project. However, EPA conducted sensitivity analysis of diet fractions (EPA 2009b) and found that these parameters contribute less than 3% to the variance in predicted tissue

[16] The sensitivity analysis uses correlation analysis of Monte Carlo simulation output to determine relative contribution to variance. Excluding log Kow results in greater relative variance attributed to other parameters.

concentrations for any given trophic level. In addition, feeding preferences are known to be insensitive unless they include large changes in trophic status (Gobas and Arnot 2005).

6.2 Uncertainty

Model *uncertainty* is used to describe incomplete or imperfect knowledge about parameters, data and assumptions. Uncertainty can arise from many sources, including measurement and analytical errors for model input data and imprecise estimates for key parameters. Uncertainty analyses investigate how the model results are affected by this lack of knowledge of the true values of certain inputs and parameters.

In this report, uncertainty analyses for the fate model followed the procedures employed by Pelletier and Mohamedali (2009). Key model inputs were selected to evaluate the effect of their uncertainty on the predicted concentration of tPCB in water and sediment. The fate model inputs selected for uncertainty analysis included tPCB loads and log K_{ow}. A similar approach was used to evaluate uncertainty in the bioaccumulation model. The most sensitive parameters, as identified in the sensitivity analysis, were selected to vary in the uncertainty analysis (e.g., octanol-water partition coefficient, the lipid assimilation efficiency, water fraction in zooplankton). This same approach was used in uncertainty analysis of the San Francisco Bay bioaccumulation model (Gobas and Arnot 2005).

To quantify the uncertainty in fate model predictions based on log K_{ow} and PCB load, the model was run with three combinations of these inputs:

1. A range of low and high log K_{ow}s along with the best loading estimate of 0.672 kg yr^{-1}. The low and high log K_{ow}s (6.01 and 6.86) were based on selection of PCB-66 and PCB-153 as representative of the range in possible representative PCB congeners.
2. A range of low and high tPCB loading estimates derived from King County (2013b) – 0.333 and 0.889 kg yr^{-1}.
3. A combination of low and high log K_{ow}/tPCB loading.

To evaluate the cumulative uncertainty of select parameters and initial conditions, the bioaccumulation model was executed once using input values that generate a low estimate and again using input values that generate a high estimate. Meanwhile, all of the other model inputs were held at their "best estimate" values.

As previously discussed, PCBs were produced as a mixture of congeners with the trade name Aroclor®, each Aroclor® differed in its congener composition. While Aroclors® have been out of production since the 1970s and those that entered the environment have substantially weathered, sediment and fish tissue results from Lake Washington still have measurable quantities of recognizable Aroclors®. The most commonly detected Aroclor® in Lake Washington is 1254 (Moshenberg 2004, Era-Miller et al. 2010, King County unpublished data). This Aroclor® is dominated by pentachlorinated PCB congeners which comprised just over 55% of its mass (Frame et al. 1996). PCB-118 is a pentachlorinated congener which comprised about 10.5% of Aroclor® 1254 and has, thus, served as a good estimate of those PCB congeners bioaccumulating in the Lake Washington food web. Because other more highly chlorinated and less chlorinated congeners are also present in Aroclor® 1254 and in Lake Washington waters, there is some uncertainty over the

representativeness of PCB-118 for modeling purposes. Using the physical attributes of all possible congeners to bound the uncertainty of PCB-118's physical parameters is not reasonable because the commercial Aroclors® found in Lake Washington fish and sediments never contained some PCB congeners. For instance, Aroclor® 1254 contains less than 0.02% monochlorinated congeners and less than 0.04% nonachlorinated congeners (Frame et al. 1996). Thus, for the purposes of bounding the uncertainty of the physical properties of PCB-118, representative tetrachlorinated and hexachlorinated congeners were chosen. Aroclor® 1254 is comprised of 17.3% tetrachlorinated and 24.4% hexachlorinated congeners. The sum of tetra-, penta-, and hepta-chlorinated congeners comprise over 97% of Aroclor® 1254.

PCB-66 was selected as a representative tetrachlorinated PCB congener for the low end estimate of log K_{ow}, while PCB-153 was selected as a representative hexachlorinated congener for the high end estimate of Log K_{ow}. Together with PCB-118, these congeners represent three of the five congeners modeled for San Francisco Bay (Davis 2004). The other two congeners were a monochlorinated (PCB-18) and nonachlorinated (PCB-194) congeners. The log K_{ow}s of PCB-66 and PCB-153 at the mean lake water temperature are 6.18 and 7.09, respectively (Table 30). These log K_{ow}s plausibly bound the uncertainty of the models with respect to the representativeness of PCB-118's log K_{ow} of 6.86 at the mean lake water temperature.

Input parameters for the bioaccumulation model are based on site-specific empirical data, general experimental data, and assumptions based on professional judgment. All of these sources have associated uncertainties of variable magnitude. For example, the mean estimated Lake Washington water temperature is based on the volume-weighted average of measurements at multiple depths over 10 years and, therefore, is likely to have relatively low uncertainty compared to the fraction of pore water ingested by mysids which has not been measured.

The most sensitive parameters identified in the sensitivity analysis (those contributing greater than 20% to variance) were selected to estimate uncertainty in the bioaccumulation model: Log K_{ow}, lipid assimilation efficiency in fish and crayfish; tPCB concentration in water; water fraction in copepods, amphipods/isopods, and daphnids. In addition, the tPCB concentration in sediment was added to the uncertainty analysis because of the suspected bias in the empirical estimate of the mean (Section 4.1.3.3). Because the non-lipid organic matter (NLOM) fraction in biota is a derived value from the water and lipid fractions, it was not included in the uncertainty analysis. Its value will vary with that of the water fraction. The most important source of uncertainty is the Log K_{ow} due to the substantial contribution of this parameter to variance in the model output.

Lipid absorption efficiency is a fraction limited to values between 0 and 1. The study providing the best estimate of lipid absorption efficiency in fish reported a very small (~1%) standard error (Gobas et al. 1999). Thus, a low and high estimate for lipid assimilation efficiency in fish was set to 0.91 and 0.93 (Table 30).

Lipid absorption efficiency in aquatic invertebrates is highly variable (15-96%) and dependent on food quality and species digestive physiology (Arnot and Gobas 2004). For example, invertebrate taxa like worms have low assimilation efficiencies and feed on high

quantities of poor quality substrate (i.e., sediment). The best estimate of invertebrate lipid assimilation efficiency used in the model was a general value representing all invertebrates. Compared to other invertebrates, crayfish feed on high quality food (e.g., other crayfish, phytoplankton). Thus, it is likely that their lipid assimilation efficiency is on the high end of the range. For the uncertainty analysis, the low estimate for crayfish was set to 0.55 and the high estimate at 0.95 (Table 30).

The estimated water fractions for copepods, amphipods/isopods and daphnids were calculated from measured solids fractions in six zooplankton and six daphnid composite samples collected from Lake Washington (Appendix A). Thus, the daphnid specific solids data were used to estimate the water fraction for daphnids and the solids data from the zooplankton samples were used to estimate the water fraction for copepods and amphipods/isopods. The minimum and maximum values from these data were used as high and low values, respectively, due to the inverse relationship between water fraction in biota and predicted tissue concentrations (Table 30). NLOM fractions for copepods, amphipods/isopods, and daphnids and all other taxa were derived from the fractions assumed for lipids and water. Thus, if the water fraction is changed, the corresponding NLOM fraction will change.

Table 30. Input values for parameters varied in uncertainty analysis

Parameter	Value for Low Estimate	Value for High Estimate
Log Kow @ 10.9˚C (PCB Congener)	6.18 (PCB - 66)	7.09 (PCB - 153)
Lipid Absorption Efficiency in Fish	0.91	0.93
Lipid Absorption Efficiency in Crayfish	0.55	0.95
Water tPCB Concentration (pg/L)	47	126
Sediment tPCB Concentration (ug/Kg dw)	9.1	24
Water Fraction in Copepods and Amphipods/Isopods	0.90	0.88
Water Fraction in Daphnids	0.93	0.91

Model predictions using the low and high estimates yielded a range of possible outcomes and revealed whether uncertainty in the true value of the parameter, load or initial condition had a significant effect on predictions of tPCB concentrations in water, sediment or biota. This report documents the parameters that were tested and identifies any parameters that have great uncertainty.

7.0 RESULTS AND DISCUSSION

A discussion of the model results, including model performance, sensitivity, and uncertainty are presented for the fate and bioaccumulation models below. The results of the fate model are discussed first as some of the results from the fate model are used in the evaluation of the bioaccumulation model.

7.1 Fate Model

The sections below describe the evaluation of the performance of the fate model (comparisons of model output to estimated tPCB concentrations and mass based on observed values), the sensitivity of the model predictions to changes in model input parameters and an evaluation of model uncertainty.

7.1.1 Performance

The performance of the fate model was evaluated by using the model in hindcast mode (see Oram et al. 2008). In hindcast mode, the model was set up with no tPCB in lake water or sediment. The model was run for 100 years under continuous loading which provided a prediction of the steady-state concentration (and mass) of tPCB in water and sediment at the end of the simulation.

Using the best estimate of tPCB loading to Lake Washington (0.672 kg yr^{-1}) and the model inputs describe above in Section 4.0, including tPCB chemical properties represented by PCB-118, the model predicts water and sediment concentrations that are similar to the estimated average tPCB concentrations in water and sediment (Figure 6). Average water concentrations were predicted to be slightly higher, but within 3 percent of the estimated mean water concentration (95 vs 92 pg/L) and lower, but within 70 percent of the estimated mean sediment concentration (18 vs 55 µg/kg dw).

It was not expected that the model predictions would so closely match the best available estimates of mean water and sediment concentrations considering the simple assumptions used by the model (single well mixed box, treating many PCB congeners with a range of chemical properties as a sum with the chemical properties of one particular PCB congener, etc.) and uncertainty in external loading. Therefore, the relatively large difference between modeled sediment tPCB concentrations was not unexpected. However, it was previously noted that the observed mean sediment tPCB concentration may be biased high due to the non-random nature of the available data – a subset of sample locations were selected to represent the influence of suspected contamination sources and many of the samples penetrated to the 10-cm sediment depth, which would capture higher levels of contamination buried below less contaminated surface sediments.

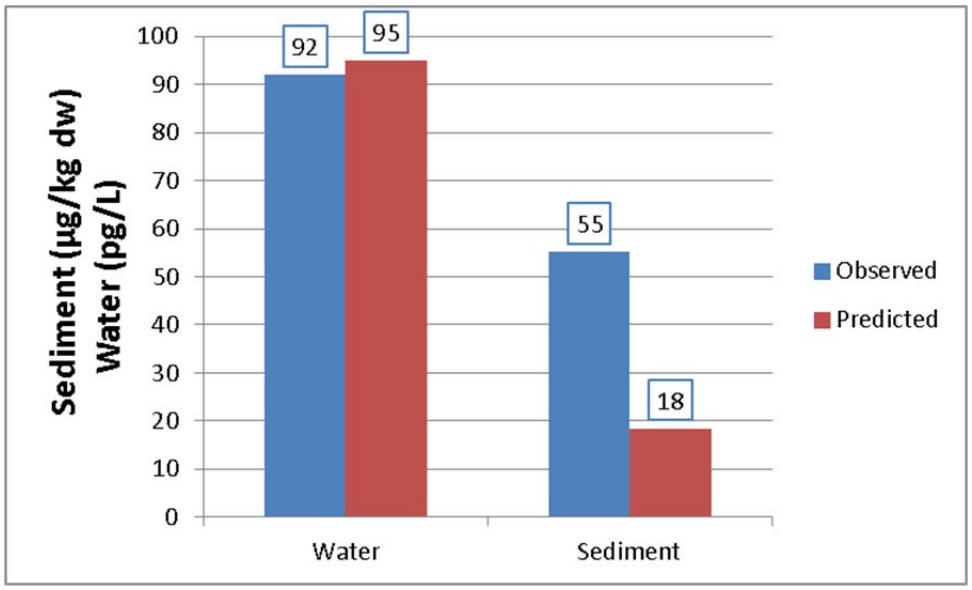

Figure 6. Comparison of fate model-predicted water and sediment concentrations to estimated average concentrations based on observed data.

In order to include an estimate of the uncertainty in the observed data in comparison to the model predictions, figures showing the 100-yr hindcast simulation were created that included vertical lines representing the mean water and sediment concentrations as well as the median (50th-percentile) and 25th and 75th percentile concentrations (Figure 7 and Figure 8). The close match between the predicted mean lake tPCB concentration and the volume-weighted mean concentration estimated from the observed data is illustrated in Figure 7. Also shown in Figure 7 is the predicted dissolved tPCB concentration, which was 75 pg/L or about 80 percent of the total tPCB concentration at steady-state (i.e., at the end of the 100-year simulation). The percent of tPCB in the dissolved phase predicted by the model at steady-state is within the range of estimates observed in the field data collected as part of this study (King County 2013a).

Figure 8 shows that although the modeled active sediment layer tPCB concentrations do not closely match the mean tPCB concentrations estimated from observed concentrations, the prediction is between the 25th- and 75th-percentile concentrations based on 69 samples collected from the lake (see Table 5 above in Section 4.0) and was slightly lower but within 20 percent of the median (50th-percentile). Note that the observed mean concentration is greater than the observed 75th-percentile concentration, indicating the strong skew in the available observed sediment tPCB concentration data. As noted above and in King County (2013c), this is likely due to a combination of bias toward sampling suspected hot spots and samples that penetrate below the active sediment layer to the depth where historical tPCB sediment contaminant levels are highest.

Note that although the predicted steady-state concentration of tPCB dissolved in sediment pore water normalized to the concentration of dry sediment is very small (1.3×10^{-4} µg/kg dw) (Figure 8), the model predicts a dissolved tPCB concentration of 130 pg/L based on the volume of pore water in the active sediment layer. No estimate of sediment pore water

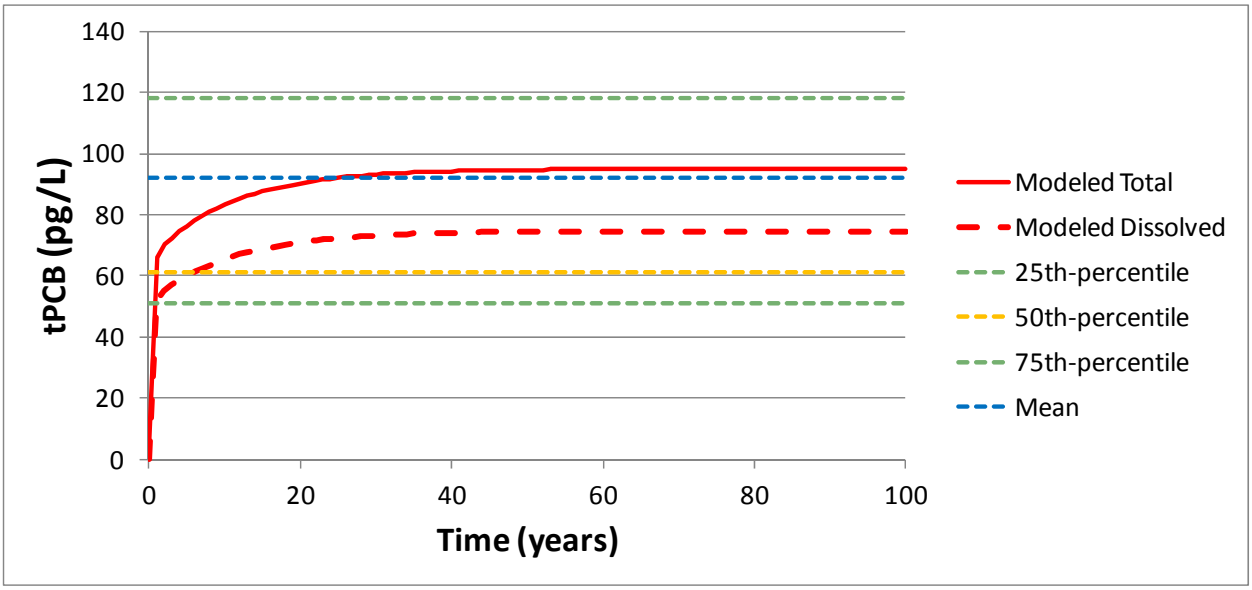

Figure 7. **Hindcast model predictions of total and dissolved tPCB concentration in lake water from initial sediment and water concentration of zero and a steady loading rate of 0.672 kg yr^{-1}. Also included are lines representing a statistical summary of the available observed concentration data (mean, 25th, 50th, and 75th percentiles).**

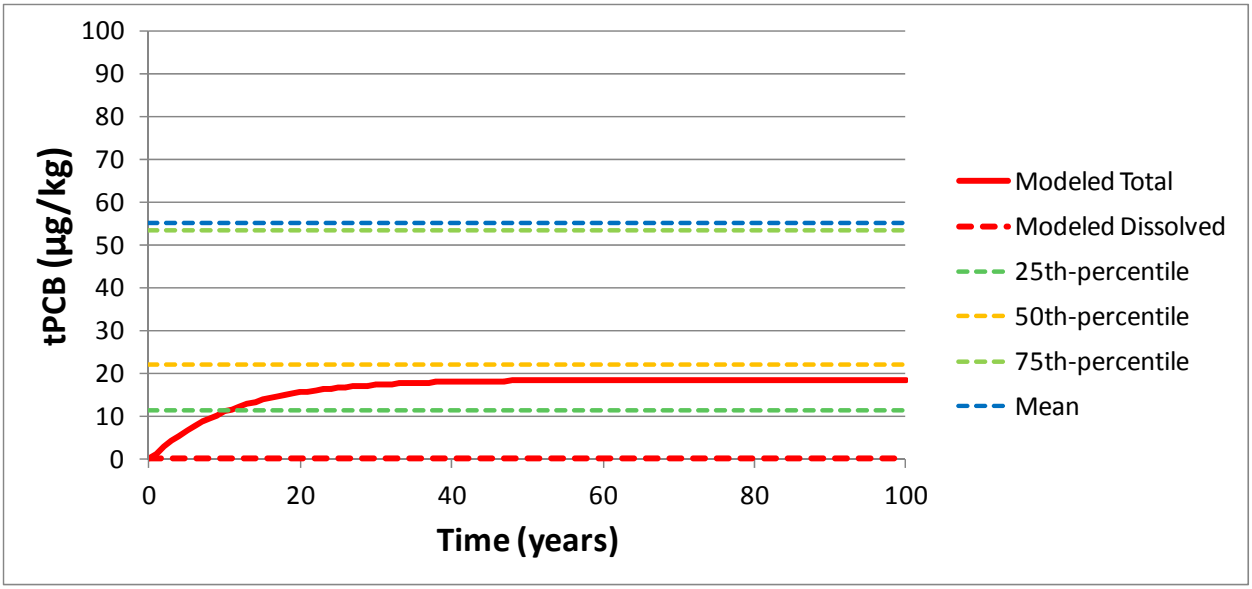

Figure 8. **Hindcast model predictions of total and dissolved tPCB concentration in lake sediment from initial sediment and water concentration of zero and a steady loading rate of 0.672 kg yr^{-1}. Also included are lines representing a statistical summary of the available observed concentration data (mean, 25th, 50th, and 75th percentiles).**

tPCB is available from this study. Available porewater data from other systems generally represent more heavily contaminated sediments (Booij et al. 2003, Hawthorne et al. 2011, Lu et al. 2011, Martinez et al. 2013) making even general comparisons difficult. However,

data presented in Booij et al. (2003) and Hawthorne et al. (2011) suggest that the model-predicted concentration is within a factor of two or less, which is consistent with the predictions of water column and sediment concentrations. Booij et al. (2003) also compared pore water to overlying water concentrations and found pore water to overlying water concentrations near one, which is also relatively consistent with the model predictions. As noted above, and as evidenced by the literature cited, sediment water partitioning models are an active area of research. Testing of the current model (and alternative models) would require the collection of relevant data specific to Lake Washington sediments.

Figure 9 illustrates the results of the 100-yr hindcast simulation predicting the mass of tPCB in water and sediment over the period of simulation. The predicted steady-state total mass of tPCB in Lake Washington was 4.9 kg, which was within the 25th and 75th-percentile estimates of the total mass in the water column and active sediment layer and somewhat lower, but within 20 percent of the median (50th-percentile) estimated mass of tPCB in the lake (Figure 9).

Note that observed tPCB data indicate that the majority of the mass of tPCB is contained in the sediments – about 98 percent. This is relatively consistent with the steady-state model results, which predicted that 95 percent of the tPCB mass was contained in the active sediment layer. These results are consistent with other studies that have shown that hydrophobic compounds like tPCBs tend to accumulate in bottom sediments (e.g., Gobas et al. 1995, Davis 2004).

Because sediment tPCB dominates the total mass of tPCB in the lake, the skew noted in the sediment tPCB data carries through to the estimated total mass of tPCB in the lake so that the mean estimated tPCB mass is slightly greater than the 75th-percentile mass (Figure 9). The model-predicted total tPCB mass is much lower than, but within 70 percent of the estimated mean total mass (4.9 vs 15 kg).

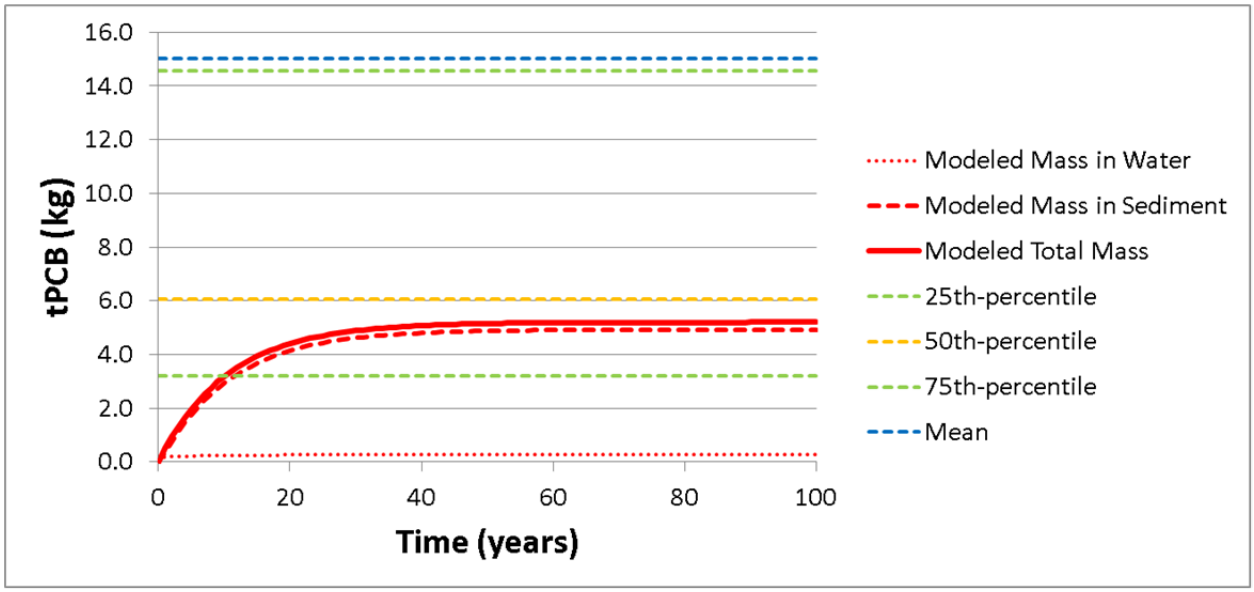

Figure 9. Hindcast model predictions of the total mass of tPCB in water and sediment h an wit initial sediment and water concentration of zero and a steady loading rate of 0.672 kg yr^{-1}. Also included are lines representing a statistical summary of the available estimates of observed tPCB mass (mean, 25th, 50th, and 75th percentiles).

Another test of the model performance that can be made is a comparison of the model-predicted and observed export of tPCB through the lake outlet at the Montlake Cut (based on measured concentrations and estimated outlet flow rate). Although there is an apparent skew in the observed tPCB concentrations at the Montlake Cut location (the mean and 75th-percentile tPCB export rates are the same), the model-predicted export of tPCB is within the 25th and 75th percentile estimates (Table 31).

Table 31. Comparison of modeled and observed tPCB export via the Lake Washington outlet at Montlake Cut (kg yr^{-1}).

Modeled	Estimated Export based on observations [a]			
	Mean	Percentiles		
		25th	50th	75th
0.118	0.140	0.073	0.110	0.140

[a] *from King County (2013b)*

Figure 10 illustrates the relative importance of the various loss pathways predicted by the model over the 100-yr hindcast simulation initialized with the steady-state predicted water and sediment concentrations. At the end of the 100-year simulation when the lake loss pathways have reached steady-state, the model predicts that the dominant loss pathway is deep burial in sediment (44 percent). Volatilization and export via the lake outlet are

predicted to be the second two most significant loss pathways after burial (24 and 16 percent, respectively). Degradation in water and sediment is the least significant loss pathway (about 9 percent).

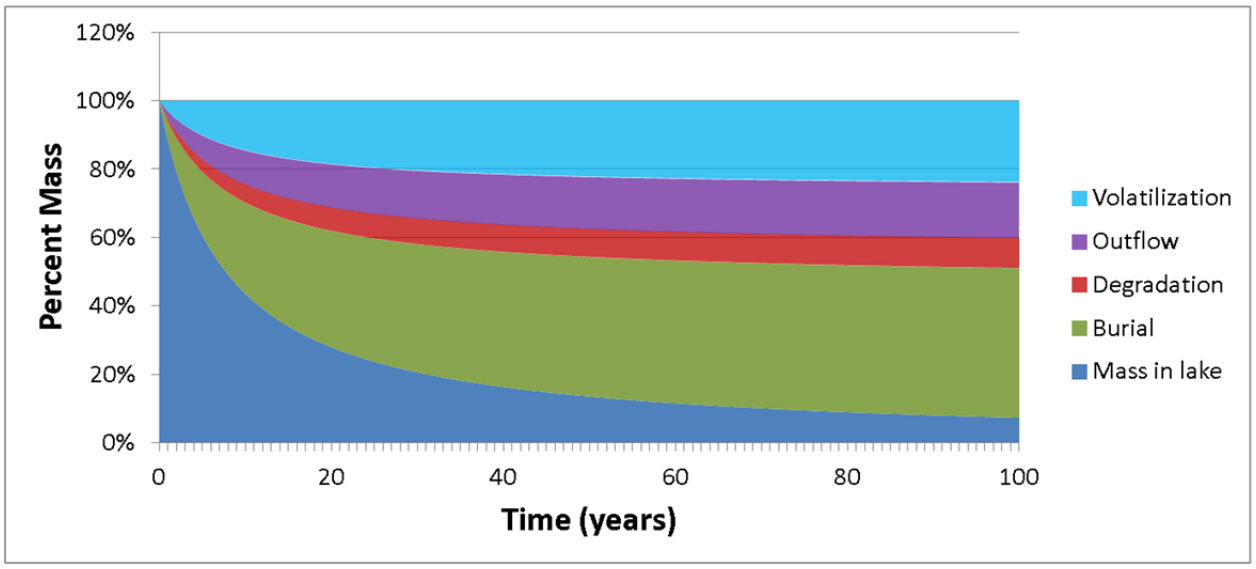

Figure 10. Hindcast model predictions of losses through different pathways based on an initial sediment and water concentration of zero and a steady loading rate of 0.672 kg yr^{-1}.

7.1.2 Sensitivity

The sensitivity of the fate model to 21 of the parameter values, specified in Tables 3 and 4, was evaluated using YASAIw. Parameters that were generally known and invariant (e.g., lake volume and surface area) were excluded from the sensitivity analysis.

The sensitivity of the model was evaluated with respect to two responses:

1. Predicted steady-state tPCB mass at the end of the 100 year simulation (based on the initial tPCB load of 0.672 kg yr^{-1} and no initial sediment or water tPCB contamination)
2. Predicted percent of tPCB mass remaining in 20 years based on the initial predicted steady-state mass of tPCB in water and sediment and a 50 percent reduction in the initial tPCB load of 0.672 kg yr^{-1}

Each of these sensitivity analyses was evaluated with respect to the total mass in the lake as well as the mass in water and sediment. This approach is similar to that used by Davis (2004) to explore the sensitivity of the PCB box model of San Francisco Bay.

7.1.2.1 Sensitivity to Predicted Steady-State Mass

The results of the sensitivity analysis of the model to the predicted steady-state mass at the end of the 100 year simulation are provided in Table 32. The predicted steady-state total tPCB mass in the lake is overwhelmingly most sensitive to the selected log K_{ow} (octanol-water partitioning coefficient) at 25 ˚C, which contributes over 90 percent of the total

variance in the predicted total tPCB mass. The second most sensitive parameter was the selected tPCB load, which contributed about 3 percent to the total variance in predicted total tPCB mass in the lake. The remaining parameters individually contributed less than 1 percent to the sensitivity of the predicted total tPCB mass. Because the majority of the tPCB is contained in the sediment, the sensitivity of the model to the predicted tPCB mass in sediment was very similar to the sensitivity of the model to the predicted total lake mass – about 92 and 3 percent of the variance in modeled sediment tPCB mass was attributed to log K_{ow} and tPCB load.

The sensitivity of the model-predicted mass of tPCB in the water column was somewhat different than for the other two model endpoints evaluated. The predicted water column tPCB mass was much less sensitive to log K_{ow} (only about 5 percent contribution to the variance in the predictions) and most sensitive to the tPCB load (~37 percent contribution to the variance in predictions). The model-predicted water mass was also moderately sensitive (greater than 5 percent contribution to variance) to a larger number of parameters, including the concentration of suspended solids and the sediment solids concentration (~10 percent each), the sediment burial coefficient (~9 percent), the proportionality constant for phase partitioning to POC (~8 percent), the DOC concentration (~7 percent) and the average wind speed (~6 percent).

The model was relatively insensitive to a number of inputs (less than 1 percent contribution to output variance), including depth of the active sediment layer, water temperature, organic carbon fraction of bottom sediment, solids settling rate and others. The relative insensitivity of the model to water temperature suggests that development of a seasonally stratified two layer water compartment model with different temperatures would not substantially change the overall tPCB mass balance or concentrations predicted by the model. A test using different mean temperatures for volatilization (14 ^{o}C), adjustment of water column K_{ow} (10.9 ^{o}C) and adjustment of sediment K_{ow} (8 ^{o}C), which are reasonable approximations of the annual mean epilimnetic, whole lake and hypolimnetic lake temperatures had a negligible effect on the model results.

There were also some interesting differences in the sign of the correlations between specific parameters and predicted steady-state total, sediment and water mass. For example, even though the predicted water mass was relatively sensitive to and positively correlated with the suspended solids concentration (i.e., higher suspended solids concentration meant higher water mass of tPCB), the predicted sediment mass was fairly insensitive, but negatively correlated with the suspended solids concentration. Regardless, the total mass of tPCB in the lake was driven by the predicted sediment tPCB mass.

7.1.2.2 Sensitivity of Predicted Mass in 20 years

Results of the sensitivity analysis of the model to the predicted response of a 50 percent reduction in tPCB loading in 20 years are provided in Table 33. The sensitivity of the model to the predicted reduction in total and sediment tPCB mass was generally very similar to the results of the sensitivity of the model to predicted steady-state tPCB mass (see Table 32). Both of these endpoints were most sensitive to log K_{ow} – with greater than 90 percent contribution to the variance in predicted mass. The second largest contribution to

the variance in predicted percent of total and sediment mass remaining after 20 years was the tPCB loading rate. The predicted percent of the initial water mass in 20 years was most sensitive to the tPCB load (~37 percent contribution to the variance in predicted percent of initial tPCB mass in water). The model was secondarily sensitive to the suspended solids concentration (~14 percent contribution to variance in model predictions). Also as in the first sensitivity analysis, the sensitivity of the model to the predicted total mass was driven primarily by the sensitivity of the predictions of sediment mass. For example, note opposite signs of the correlation and contributions to variance of the input suspended solids concentration (Table 33).

Table 32. Comparison Summary of sensitivity analysis results of the fate model to predicted steady-state mass of tPCB in Lake Washington.

Parameter	Predicted Total Mass		Predicted Water Mass		Predicted Sediment Mass	
	Spearman's rho	Contribution to Variance	Spearman's rho	Contribution to Variance	Spearman's rho	Contribution to Variance
Log Kow @ 25 ^{o}C	0.9313	91.48%	0.2082	4.95%	0.9326	91.65%
PCB load (kg/yr)	0.1752	3.24%	0.5673	36.74%	0.1655	2.89%
Sediment burial coefficient (m/d)	-0.0932	0.92%	-0.2779	8.82%	-0.0881	0.82%
Depth of active sediment layer (m)	0.0908	0.87%	-0.0349	0.14%	0.0924	0.90%
Concentration of solids in sediment (kg/L)	0.0898	0.85%	-0.2929	9.80%	0.0965	0.98%
Average wind speed at 10 m height (m/s)	-0.0782	0.64%	-0.2199	5.52%	-0.075	0.59%
Proportionality constant for phase partitioning to POC	0.0592	0.37%	-0.257	7.54%	0.0646	0.44%
Particulate organic carbon in water column (kg/L)	0.0540	0.31%	-0.1718	3.37%	0.058	0.35%
Organic carbon fraction of bottom sediment	0.0538	0.31%	0.0331	0.12%	0.0528	0.29%
Temperature of water (^{o}C)	-0.0486	0.25%	-0.0579	0.38%	-0.0481	0.24%
Suspended solids concentration (kg/L)	-0.0391	0.16%	0.302	10.41%	-0.0451	0.21%
Degradation in water (1/d)	0.0336	0.12%	0.0469	0.25%	0.0329	0.11%
Dissolved organic carbon in water column (kg/L)	-0.0329	0.11%	0.2388	6.51%	-0.038	0.15%
Water outflow (L/d)	-0.0329	0.11%	-0.0764	0.67%	-0.0319	0.11%
Solids settling rate (m/d)	-0.0283	0.08%	-0.0485	0.27%	-0.027	0.08%
Density of sediment organic carbon (kg/L)	-0.0230	0.06%	0.0011	0.00%	-0.0228	0.05%
Degradation in sediment (1/d)	-0.0202	0.04%	0.0217	0.05%	-0.0208	0.05%
Sediment porosity (fraction)	0.0176	0.03%	0.0232	0.06%	0.0172	0.03%
Henry' Law constant (Pa m^3/mol)	-0.0149	0.02%	-0.0383	0.17%	-0.0144	0.02%
Water-to-sediment diffusion coefficient (m/d)	0.0117	0.01%	-0.0181	0.04%	0.0125	0.02%
Proportionality constant for phase partitioning to DOC	0.0110	0.01%	0.1917	4.19%	0.0071	0.01%

Table 33. Summary of sensitivity analysis results of the fate model to predicted percent of initial mass of tPCB in Lake Washington remaining in 20 years following a 50 percent reduction from the current best estimate loading rate.

Parameter	Predicted % of Initial Total Mass in 20 yrs		Predicted % of Initial Water Mass in 20 yrs		Predicted % of Initial Sediment Mass in 20 yrs	
	Spearman's rho	Contribution to Variance	Spearman's rho	Contribution to Variance	Spearman's rho	Contribution to Variance
Log Kow @ 25 ^{o}C	0.9382	90.95%	0.1476	2.49%	0.9402	91.24%
PCB load (kg/yr)	0.1763	3.21%	0.5694	37.12%	0.1653	2.82%
Sediment burial coefficient (m/d)	-0.1180	1.44%	-0.2445	6.84%	-0.1131	1.32%
Proportionality constant for phase partitioning to POC	0.1029	1.09%	-0.247	6.98%	0.1089	1.22%
Temperature of water (^{o}C)	-0.1015	1.06%	-0.0735	0.62%	-0.0998	1.03%
Concentration of solids in sediment (kg/L)	-0.0662	0.45%	-0.2758	8.71%	-0.062	0.40%
Suspended solids concentration (kg/L)	-0.0630	0.41%	0.3534	14.30%	-0.072	0.53%
Particulate organic carbon in water column (kg/L)	0.0625	0.40%	-0.2246	5.78%	0.0684	0.48%
Average wind speed at 10 m height (m/s)	-0.0513	0.27%	-0.1907	4.17%	-0.0485	0.24%
Degradation in water (1/d)	0.0395	0.16%	0.0538	0.33%	0.0388	0.16%
Water outflow (L/d)	-0.0371	0.14%	-0.0779	0.69%	-0.0355	0.13%
Water-to-sediment diffusion coefficient (m/d)	0.0311	0.10%	-0.053	0.32%	0.0325	0.11%
Degradation in sediment (1/d)	-0.0285	0.08%	-0.0207	0.05%	-0.0281	0.08%
Sediment porosity (fraction)	-0.0281	0.08%	0.0209	0.05%	-0.0284	0.08%
Organic carbon fraction of bottom sediment	0.0262	0.07%	0.0167	0.03%	0.0259	0.07%
Henry' Law constant (Pa m^{3}/mol)	-0.0164	0.03%	0.0115	0.02%	-0.0167	0.03%
Depth of active sediment layer (m)	-0.0119	0.01%	0.0271	0.08%	-0.0136	0.02%
Dissolved organic carbon in water column (kg/L)	-0.0081	0.01%	0.2243	5.76%	-0.013	0.02%
Solids settling rate (m/d)	0.0065	0.00%	-0.0057	0.00%	0.0065	0.00%
Density of sediment organic carbon (kg/L)	-0.0051	0.00%	0.0022	0.00%	-0.0055	0.00%
Proportionality constant for phase partitioning to DOC	-0.0031	0.00%	0.222	5.64%	-0.0085	0.01%

7.1.3 Uncertainty

Based on the preceding sensitivity analysis, the quantifiable uncertainty in the fate model is due primarily to the selected log K_{ow} and the estimated tPCB loading rate. To quantify uncertainty from these inputs, the model was run with three combinations of these inputs:

1. Range of low and high log K_{ow}s and best loading estimate of 0.672 kg yr^{-1}. Low and high log K_{ow} (6.01 and 6.86 at 25 ^{o}C / 6.18 and 7.09 at 10.9 ^{o}C) were based on selection of PCB-66 and PCB-153 as representative of the range in possible representative PCB congeners.
2. Range of low and high tPCB loading estimates derived from King County (2013b) – 0.333 and 0.889 kg yr^{-1}.
3. Combination of low and high log K_{ow}/tPCB loading.

The results of these model uncertainty tests are summarized in Table 34 for model-predicted steady-state concentrations in water and sediment. In general, it appears that although the fate model is most sensitive in a relative sense to log K_{ow}, the relatively large uncertainty in total tPCB loading to the lake is the largest driver in model prediction uncertainty. The combination of low/high tPCB loading/log K_{ow} resulted in only a small relative increase in the range of model-predicted water and sediment concentrations relative to the effect of low/high tPCB loads alone. For model-predicted total water concentrations, the low/high tPCB load range was 47 to 126 pg/L compared to a low/high load/log K_{ow} range of 44 to 128 pg/L. The contribution of the selection of log K_{ow} on the uncertainty in model-predicted sediment tPCB concentrations was a bit higher, with the prediction uncertainty range going from 9 to 24 µg/kg dw for low/high tPCB load to 4 to 28 µg/kg dw for the combination of load and log K_{ow}. In general, the range in model prediction uncertainty was within or just outside the range in the estimated uncertainty of the observed concentrations (see Table 34).

Table 34. Summary of fate model uncertainty analysis results.

	Water (pg/L)	**Sediment** (µg/kg dw)
Base case [a]	95	18
Observed 25th and 75th-percentile concentrations	51 - 118	11 - 53
Uncertainty Scenario		
Low tPCB Load (0.333 kg yr-1)	47	9
High tPCB Load (0.889 kg yr-1)	126	24
Low log K_{ow} (6.01 @ 25 ^{o}C)	89	8
High log K_{ow} (6.86 @ 25 ^{o}C)	96	21
Low load/low log K_{ow}	44	4
High load/high log K_{ow}	128	28

[a] tPCB load = 0.672 kg yr-1 and log K_{ow} = 6.65 @ 25 ^{o}C.

Figure 11 and Figure 12 provide a visual illustration of the range in model prediction uncertainty, including a comparison to the range in uncertainty of the observed data. The range in estimated model uncertainty with respect to the predicted total water concentration reflects closely the range in uncertainty in the observed mean water column concentration (Figure 11). However, the range in estimated uncertainty of predicted sediment tPCB concentration clusters more closely to the range in uncertainty of the observed sediment concentrations – near the 50th percentile and lower (Figure 12). Again, this is consistent with the hypothesis that the observed sediment concentrations are biased high due to preferential selection of sampling locations and the deeper penetration depth of many of the samples.

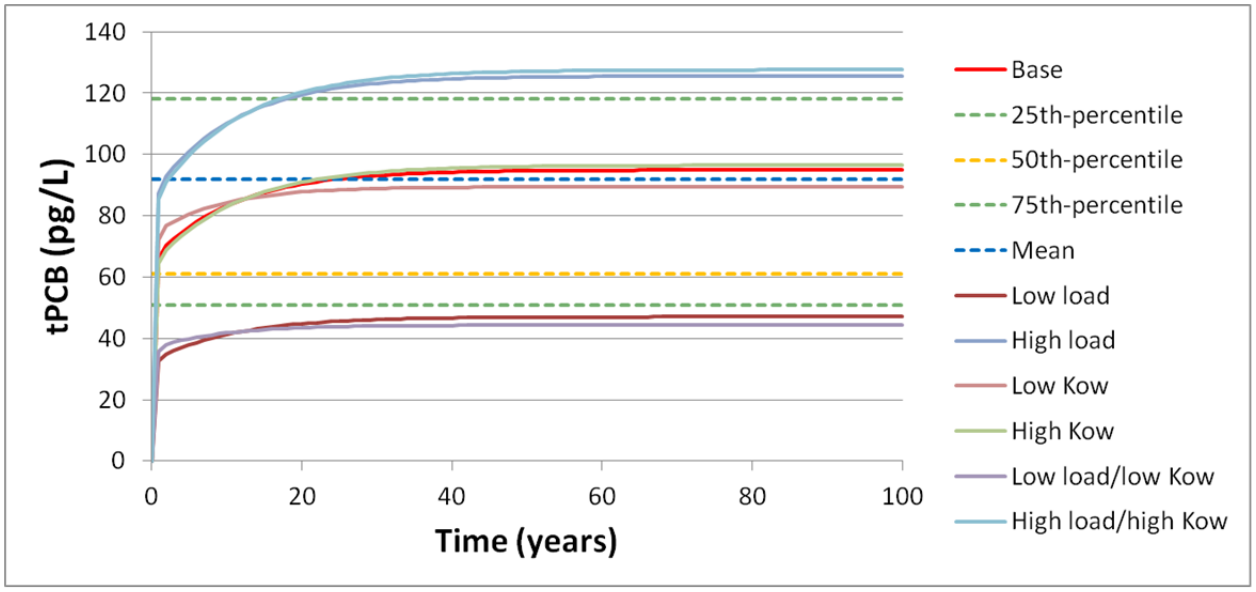

Figure 11. Uncertainty in model-predicted tPCB concentrations in water compared to uncertainty in observed concentrations based on range of possible inputs for total tPCB loading and log K_{ow}.

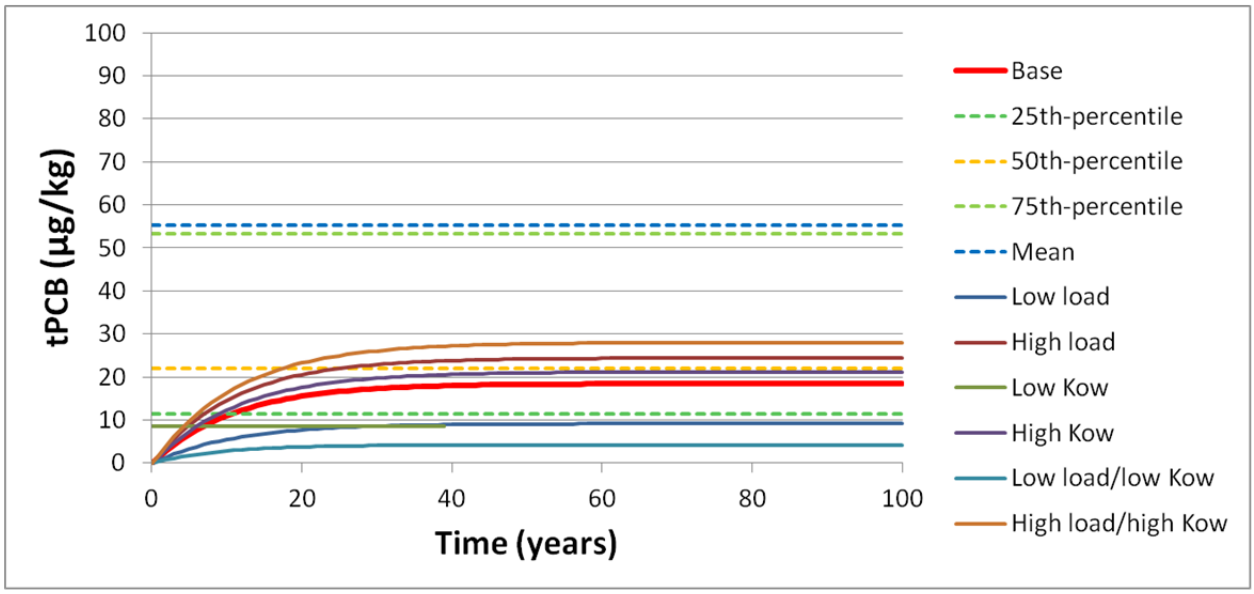

Figure 12. Uncertainty in model-predicted tPCB concentrations in the active sediment layer compared to uncertainty in observed concentrations based on range of possible inputs for total tPCB loading and log K_{ow}.

It should be noted that there are other sources of uncertainty that are more difficult to quantify. These sources of uncertainty potentially include missing or mis-specified processes that result primarily from necessary model simplifications of natural systems. One particular source of potential uncertainty that cannot be easily quantified is the specification of the type of sediment and water partitioning approach used in the model. Current research has focused on multi-phase partitioning models, with the goal of improving the certainty in model predictions (e.g., Greene et al. 2013). However, development and evaluation of more complex water and sediment partitioning models requires more detailed site-specific data than are currently unavailable for Lake Washington.

Another source of uncertainty is the representation of Lake Washington as a single completely mixed layer forced by average inputs, including tPCB loading, wind speed and water temperature, when the lake has obviously experienced a history of PCB inputs and time-varying winds and temperatures. However, relatively simple contaminant fate models of other dynamic systems (e.g., Lake Ontario, San Francisco Bay) have been developed and described as useful management tools (Mackay et al. 1994, Gobas et al. 1995, Davis et al. 2007). Another simplification incorporated into the fate model is the omission of a compartment for biota. Based on information available in King County (2013e), the total mass of tPCB in biota is on the order of 0.2 kg, which is about 4 percent of the total predicted mass of tPCB in the lake (assuming an active sediment layer of 2.5 cm). Of the tPCB mass in biota, about 60 percent appears to be associated with obligate benthic organisms, which is where the majority of the mass of tPCB resides. As a first-approximation, it does not appear that these simplifications compromise the general estimates of the partitioning and fate of tPCB in Lake Washington.

Additional model complexity does not necessarily equate with better model fit to the data (Arhonditsis and Brett 2005) or better management decisions (Bartholow 2003). In general, this simple mass budget model supports the total tPCB loading estimate and provides an initial step towards understanding the long term fate of PCBs in the lake.

7.2 Bioaccumulation Model

This section describes the results of model testing, and sensitivity and uncertainty analyses for the bioaccumulation model.

7.2.1 Performance

Performance of the bioaccumulation model was gauged by comparison of predicted tPCB concentrations in tissue to mean observed total PCB concentrations available for the same species. This approach was used to evaluate the Puget Sound bioaccumulation model (Pelletier and Mohamedali 2009) and a variation of this approach was used to evaluate the San Francisco Bay bioaccumulation model (Gobas and Arnot 2005). The ratio of predicted to observed tissue concentrations was calculated for each modeled taxon with ratios below 1.0 indicating under-prediction and above 1.0 indicating over-prediction. Ratios were calculated for model predictions using empirically-derived mean sediment (55 µg/kg dry weight) and water (92 pg/L) tPCB concentrations and using the fate model–predicted mean sediment (18 µg/kg dry weight) and water (95 pg/L) PCB concentrations as input (Figure13).

As previously discussed, the empirically-derived mean sediment tPCB concentration is potentially biased high because a large portion of the samples in the data set were collected from the 0-10 cm depth which is deeper than the biologically active zone (Section 4.1.3.1) and likely incorporates higher concentrations near the 10 cm depth horizon that resulted from the peak of PCB input to the lake. These deeper samples had higher PCB concentrations than those collected from 0-2 cm depth (King County 2013d). Thus, the fate model-predicted sediment concentrations provide a lower, potentially more realistic estimate of the mean sediment PCB concentration. The empirically-derived and fate model-predicted water concentrations are comparable.

Model bias is calculated as the geometric mean of individual predicted/observed ratios. Model bias between 0.5 and 2.0 is considered good performance and comparable to other applications of this bioaccumulation model (Pelletier and Mohamedali 2009, Condon 2007, Gobas and Arnot 2005). Model bias under empirically-derived water and sediment input concentrations was just outside this range at 2.3 (Table 35). Individual taxon ratios were within this range for all taxa except large crayfish, small prickly sculpin, small and large yellow perch, cutthroat trout, and northern pikeminnow which were all over-predicted. However, the ratios for cutthroat trout and northern pikeminnow were less than 3.0 and those for yellow perch were less than 4.0. The large crayfish ratio was notably high at nearly 23, but was based on an observed sample size of four individuals and a detection limit-derived tPCB concentration because all observed results were nondetect.

Application of the fate model-predicted sediment and water input concentrations resulted in a model bias of 1.2 (Table 35). The longfin smelt ratio was just below 0.5 and the ratio

for large yellow perch was 3.4. The large crayfish ratio remained notably high at approximately 13. Ratios for all other taxa indicated predicted tissue concentrations were within a factor of two of observed.

Over-prediction of the large yellow perch tissue concentrations may be due to uncertainty in species and size of fish consumed. The dietary assumptions in the model are taken from McIntyre (2004) which specifies fractions of sculpin consumed but does not identify fractions of other fish species. Large yellow perch are estimated to consume an annual average of 38% other fish. For this bioaccumulation model, this fraction was divided between small yellow perch, adult threespine stickleback, adult longfin smelt, and juvenile sockeye salmon. However, bioenergetics modeling by Mazur (2004) indicated that the sizes of the modeled prey fish may overestimate PCB exposure. Mazur (2004) described large yellow perch as eating juvenile sockeye salmon but that most were in the fry stage. Also, fish eggs comprised a portion of the other fish consumed (Mazur 2004). The consumption of smelt and sculpin is congruent with Mazur's findings. If fry and fish eggs are substantial fractions of the large yellow perch diet, these fish would present lower exposure than the juvenile and adult life stages of fish consumed in the model. Hence, this could account for the over-prediction of PCB tissue concentrations.

The high over-prediction of tissue concentrations in large crayfish may reflect multiple uncertainties, namely the lack of specific diet information for Lake Washington crayfish, the limited number of samples collected to provide lipid content, body weight, and PCB concentrations, and the small range of sizes collected (King County 2013e). The uncertainties apparent here identify a data gap that could be fulfilled in future field sampling efforts.

Table 35. Predicted/observed ratios for PCB tissue concentrations modeled using empirically-derived or fate model-predicted mean sediment and water input concentrations

Modeled Taxon	Ratios - Empirical	Ratios - Modeled
Daphnia	1.0*	1.1*
Mysids	1.2*	1.1*
Crayfish Large	26.0 *	13.2*
Sockeye Salmon (juv.)	1.4	0.9
Longfin Smelt	0.9	0.4
Peamouth	1.2	0.6
Prickly Sculpin Large	1.8	0.9
Prickly Sculpin Small	4.2	1.9
Yellow Perch Large	6.9	3.4
Yellow Perch Small	3.6	1.8
Threespine Stickleback	1.1	0.5
Smallmouth Bass	1.9	0.9
Cutthroat Trout	2.8	1.3
Northern Pikeminnow	2.1	1.0
Model Bias	**2.3**	**1.2**

*Observed mean tissue concentrations are maximum detection limits because no samples had PCB detections.

Mean tissue concentrations modeled using empirically-derived water and sediment data were predicted within the standard deviation of the observed concentrations for threespine stickleback, longfin smelt, large prickly sculpin, peamouth, smallmouth bass, and northern pikeminnow (Figure 13). The mean predicted concentration of juvenile sockeye salmon is just above (90 µg/kg) the upper standard deviation of observed concentrations (82 µg/kg). Predicted tissue concentrations in cutthroat trout, small prickly sculpin and small and large yellow perch were approximately 1.5 to 5 times higher than the upper standard deviation of observed concentrations.

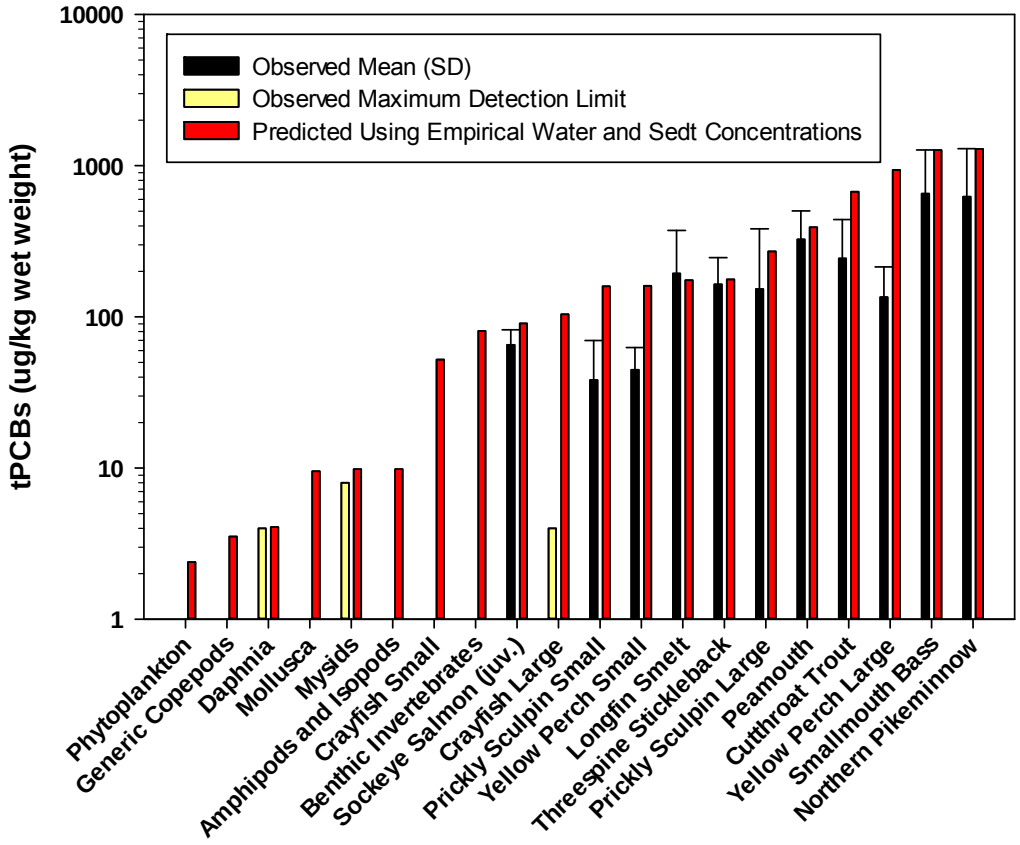

Figure 13. Model-predicted tissue concentrations using empirically-derived water and sediment PCB concentrations compared to observed tPCB tissue concentrations

Predicted tissue concentrations using fate model-predicted water and sediment concentrations were lower than observed and within one standard deviation of the mean for most fish except small prickly sculpin and small and large yellow perch which were higher, and threespine stickleback which was slightly lower (Figure 14). The main difference between modeled tissue concentrations using empirically-derived versus fate model-predicted water and sediment concentrations are due to the lower mean sediment concentration of the latter source.

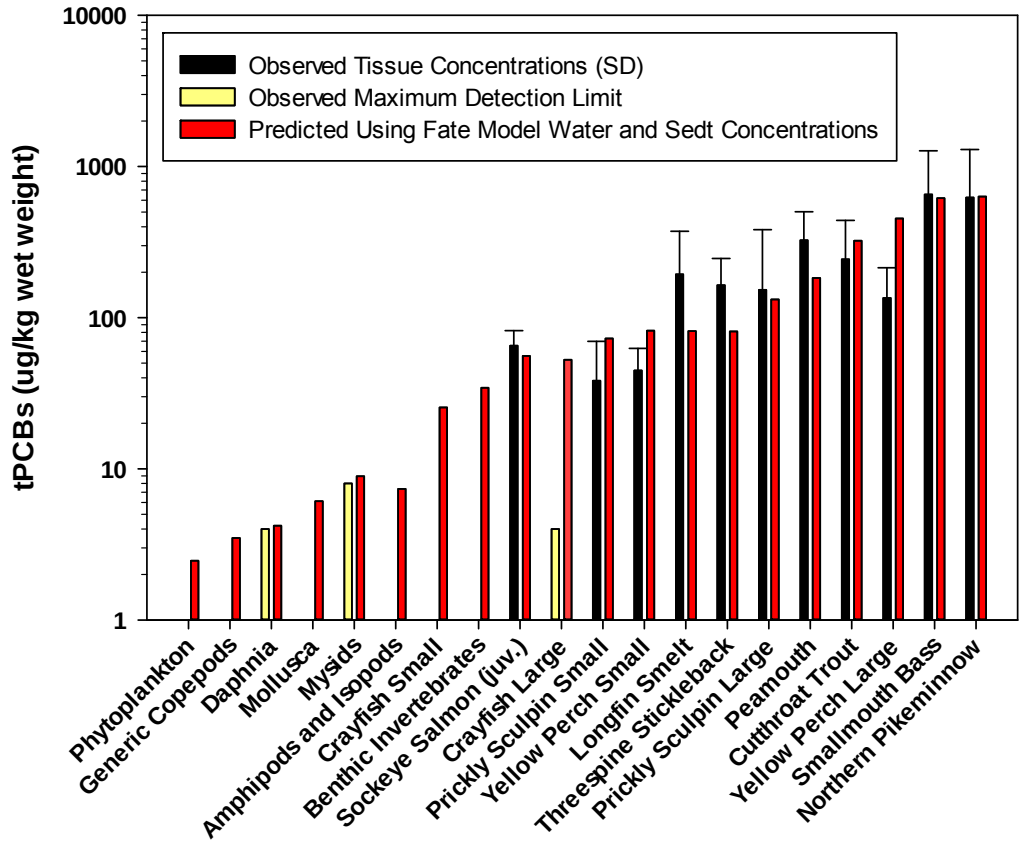

Figure 14. Model-predicted tissue concentrations using water and sediment concentrations predicted by fate model compared to observed Total PCB tissue concentrations.

Because model bias was 1.2 using the fate model-predicted water and sediment concentrations compared to 2.3 using the observed water and sediment concentrations, values of the former were used as input to the model for the sensitivity and uncertainty analyses.

7.2.2 Sensitivity

Variation of all biotic and abiotic input values, except log K_{ow} (octanol-water partitioning coefficient), by a standard deviation of 5% indicated that the dietary absorption efficiency of lipid in fish contributed to the greatest variance (42-69%) in predicted tissue concentrations (Table 36). Condon (2007) and Gobas and Arnot (2005) also found dietary absorption efficiency of lipids to be one of the most influential biological parameters in the same or similar bioaccumulation models. Other relatively sensitive parameters include the lipid assimilation efficiency in crayfish, water concentration of tPCBs (phytoplankton, mysids and daphnids[17]), the water, lipid and non-lipid organic matter fractions of

[17] Taxa in parentheses are those whose predicted tissue concentrations are sensitive to the named parameter.

invertebrates (invertebrates), sediment concentration of tPCBs (benthic invertebrates), and the aqueous phase resistance constant and growth rate constant of phytoplankton. All other parameter variations resulted in less than a 10% contribution to any single modeled taxon's tissue PCB concentration (Appendix C).

To test the sensitivity of predicted tissue concentrations to changes in water versus sediment concentrations, the sediment concentration was held constant while the water concentration was reduced by 20%. Then, the opposite was done to vary sediment input while holding the water concentration constant. Comparing the difference in predicted tissue concentrations between these two model runs and the base (i.e. no change) model run showed that the overall effect on fish tissue concentrations of changing the water was comparable to changing sediment (Table 37). This is indicative of the relatively important role that pelagic prey play in the Lake Washington food web. Although the majority of PCB mass in the lake is stored in sediment, and sediment is a key driver of bioaccumulation, PCB concentrations in water are also important as an exposure route into biota.

Table 36. Sensitivity of Predicted Tissue Concentrations to Individual Parameters Contributing Over 10% to Variance

Output	Parameter	Spearman's Rho	Contribution to variance
Yellow Perch Small	Yellow perch small: Dietary absorption efficiency of lipid	0.9108	68.60%
Cutthroat Trout	Cutthroat trout: Dietary absorption efficiency of lipid	0.8770	65.00%
Peamouth	Peamouth chub: Dietary absorption efficiency of lipid	0.7786	55.63%
Sockeye Salmon (juv.)	Sockeye juvenile: Dietary absorption efficiency of lipid	0.8400	55.41%
Prickly Sculpin Large	Sculpin: Dietary absorption efficiency of lipid	0.7988	51.40%
Prickly Sculpin Small	Prickly sculpin small: Dietary absorption efficiency of lipid	0.8089	51.28%
Longfin Smelt	Longfin smelt: Dietary absorption efficiency of lipid	0.7721	50.14%
Smallmouth Bass	Smallmouth bass: Dietary absorption efficiency of lipid	0.7718	49.73%
Northern Pikeminnow	Northern pikeminnow: Dietary absorption efficiency of lipid	0.7668	49.04%
Yellow Perch Large	Yellow perch large: Dietary absorption efficiency of lipid	0.7690	47.33%
Threespine Stickleback	Stickleback: Dietary absorption efficiency of lipid	0.7053	42.29%
Mysids	tPCBs water concentration	0.6137	32.96%
Copepods	Copepods: Water fraction in biota	-0.7360	32.25%
Copepods	Copepods: NLOM fraction in biota	0.7295	31.68%
Amphipods/Isopods	Amphipods/Isopods: Water fraction in biota	-0.7002	30.33%
Amphipods/Isopods	Amphipods/Isopods: NLOM fraction in biota	0.6949	29.86%
Phytoplankton	tPCBs water concentration	0.5878	29.81%
Daphnia	Daphnia: Water fraction in biota	-0.6114	25.02%
Daphnia	Daphnia: NLOM fraction in biota	0.5963	23.80%
Crayfish Large	Crayfish Large: Dietary absorption efficiency of lipid	0.5428	22.86%
Crayfish Small	Crayfish small: Dietary absorption efficiency of lipid	0.5236	21.54%
Crayfish Small	Crayfish small: Water fraction in biota	-0.4497	15.89%
Crayfish Small	Crayfish small: NLOM fraction in biota	0.4455	15.59%
Phytoplankton	Phytoplankton: Aqueous phase resistance constant	-0.4222	15.38%
Phytoplankton	Phytoplankton: Growth rate constant	-0.4202	15.24%
Daphnia	tPCBs water concentration	0.4730	14.97%
Mysids	Mysids: Lipid fraction in biota	0.4108	14.77%
Mollusks	Mollusks: Water fraction in biota	-0.4162	12.78%
Benthic Invertebrates	Benthic invertebrates: Lipid fraction in biota	0.3966	12.78%
Benthic Invertebrates	tPCBs sediment concentration	0.3934	12.57%
Benthic Invertebrates	Benthic invertebrates: Dietary absorption efficiency of lipid	0.3911	12.43%
Mollusks	Mollusks: NLOM fraction in biota	0.4033	11.99%
Yellow Perch Large	Sculpin: Dietary absorption efficiency of lipid	0.3828	11.73%
Crayfish Large	Crayfish Large: Water fraction in biota	-0.3851	11.51%
Mollusks	Mollusks: Lipid fraction in biota	0.3927	11.38%
Crayfish Large	Crayfish Large: NLOM fraction in biota	0.3821	11.33%
Benthic Invertebrates	Benthic invertebrates: Water fraction in biota	-0.3696	11.10%
Benthic Invertebrates	Benthic invertebrates: NLOM fraction in biota	0.3529	10.12%

NLOM = non-lipid organic matter fraction

Table 37. Sensitivity of Bioaccumulation Model to Change in Water and Sediment Concentrations

Organism	Base	Sediment <20%	Water <20%
Phytoplankton	2.5	2.47	1.98
Daphnia	4.2	4.21	3.37
Mysids	8.9	8.83	7.27
Generic Copepods	3.5	3.47	2.80
Amphipods and Isopods	7.4	7.12	6.17
Mollusca	6.1	5.75	5.23
Crayfish	52.8	47.76	47.34
Benthic Invertebrates	34.4	29.83	32.08
Crayfish Small	25.5	22.83	23.02
Sockeye Salmon (juv.)	56.0	52.47	48.24
Threespine Stickleback	81.3	71.79	74.47
Longfin Smelt	81.5	72.25	74.40
Peamouth	183.5	162.87	167.35
Prickly Sculpin Large	132.4	118.63	119.63
Yellow Perch Large	454.0	406.22	411.05
Smallmouth Bass	619.4	555.38	559.47
Cutthroat Trout	323.0	288.48	292.87
Northern Pikeminnow	632.8	567.86	571.11
Prickly Sculpin Small	73.1	64.60	67.00
Yellow Perch Small	82.1	74.30	73.47

7.2.3 Uncertainty

Based on results of the sensitivity analysis, the following input values were varied to give a low and high estimate for the model uncertainty analysis: Log K_{ow}, lipid assimilation efficiency in fish and crayfish, tPCBs concentration in water and sediment, and water fraction in copepods, amphipods/isopods, and daphnids. Low and high estimates of predicted tissue concentrations compared to the predicted best estimate and observed mean ±SD are presented in Table 38 and Figure15. The range of these estimates reflects a cumulative contribution of uncertainty from the most important sources. Other, more minor sources of uncertainty may nominally impact the range of predicted tissue concentrations, but may also cancel each other out.

The predicted low and high estimates are within a factor of five for phytoplankton, daphnia, copepods, mollusks, amphipods/isopods, and mysids. The range widens for benthic invertebrates, crayfish, and fish. Comparing the predicted low and high estimates to the range of observed tissue concentrations suggests that uncertainty in the observed data is greater than that associated with key model inputs for longfin smelt, large prickly sculpin, peamouth, smallmouth bass, cutthroat trout, and northern pikeminnow. Overall, the predicted best estimates are within a factor of two of the high estimate of uncertainty and within a factor of approximately 5-10 of the low estimate of uncertainty. Thus, reducing uncertainty is more likely to lower than raise the best estimate.

The data used to estimate the observed tissue concentrations have their own sources of uncertainty. Observed tissue concentrations and sample sizes were summarized in King

County (2013e). Sampling methods used by the different studies were adequately diverse and the analytical laboratories were state-certified resulting in minimal bias from these sources. However, there are notable weaknesses in the observed tissue concentration data set which may present bias. These weaknesses include:

- PCB data are very limited for invertebrates and for many invertebrate taxa, data are not available.
- tPCBs were not detected in daphnid, signal crayfish, or mysid samples. Observed concentrations are represented by the highest maximum detection limit (MDL).
- Only four individual signal crayfish and eight whole individual smallmouth bass samples were analyzed for tPCBs resulting in small sample sizes and high uncertainty in the observed estimate of tissue concentrations for these species. No composite samples were analyzed for these species.
- McIntyre (2004) analyzed three and King County (2013e) analyzed five smallmouth bass. tPCB concentrations in the three samples from McIntyre (2004) were similar (303-425 ug/kg wet weight). However, tPCB concentrations in the five King County samples ranged greatly (63-1,755 ug/kg wet weight) presenting high uncertainty in the observed tPCB estimate for smallmouth bass.

As discussed in Section 5.3, the most notable sources of uncertainty for dietary preferences are the lack of Lake Washington specific information for crayfish, the incongruence between the threespine stickleback diet and the stable nitrogen isotope signature, the lack of biological information regarding fish egg and larvae consumed by fish, and the high variability of tPCB concentrations observed in smallmouth bass.

Table 38. Range of uncertainty in predicted compared to observed (mean ±SD) tissue concentrations (µg/kg wet)

Organism	Predicted Low Estimate	Predicted Best Estimate	Predicted High Estimate	Observed Mean ±SD
Phytoplankton	1.31	2.47	2.50	N/A
Daphnia	1.03	4.21	6.11	N/A
Copepods	0.81	3.48	5.24	N/A
Mollusks	2.09	6.10	7.84	N/A
Amphipods/Isopods	1.51	7.38	10.99	N/A
Mysids	2.63	8.94	11.75	N/A
Benthic Invertebrates	7.87	34.40	51.81	N/A
Crayfish Small	3.87	25.47	63.32	N/A
Crayfish Large	5.97	52.84	178.94	N/A
Sockeye Salmon (juv.)	9.60	55.95	82.68	48-82
Threespine Stickleback	17.74	81.25	116.17	82-247
Longfin Smelt	18.31	81.48	115.72	15-373*
Prickly Sculpin Large	15.97	132.37	235.70	0-382*
Prickly Sculpin Small	9.12	73.11	125.98	6.7-70
Peamouth	40.14	183.45	260.18	149-502*
Yellow Perch Large	60.80	454.04	746.91	56-214
Yellow Perch Small	13.25	82.09	126.65	27-63
Smallmouth Bass	80.96	619.36	1129.20	35-1271*
Cutthroat Trout	51.82	322.97	500.05	47-441*
Northern Pikeminnow	86.79	632.76	1080.93	0-1294*

SD – standard deviation

*observed mean±SD range is greater than predicted low/high estimates

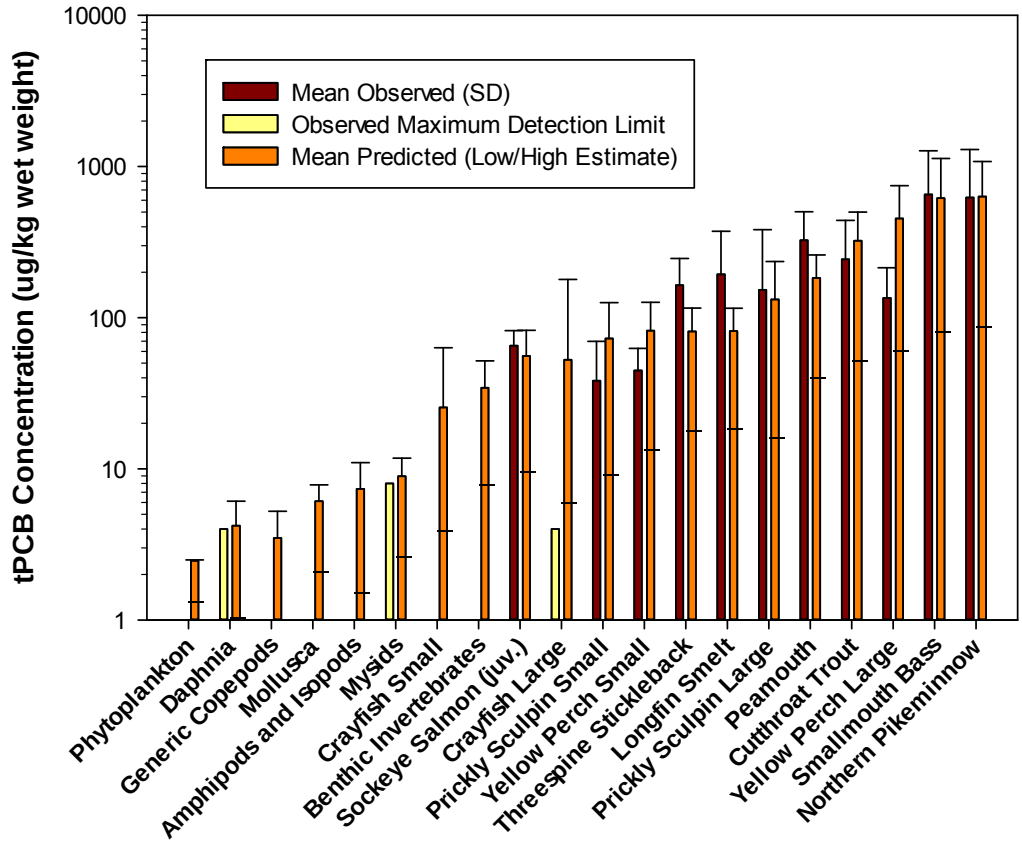

Figure 15. Low and high uncertainty estimates for the Lake Washington bioaccumulation model

8.0 CONCLUSIONS

This report described the development and performance of a fate model and bioaccumulation model of PCBs in Lake Washington. Although the fate model is a simple, two-compartment box model (water and sediment), it performed well in hindcast testing against observed water and sediment concentrations. This test supports the assumptions made to develop the model, but most importantly these results also support the tPCB loading estimate derived by this study as a reliable first-approximation of the current tPCB loading rate to the lake. The predicted equilibrium water and sediment tPCB concentration closely match the best estimates of current conditions in Lake Washington. The predicted equilibrium sediment tPCB concentration was approximately three times lower than the best estimate based on empirical data. However, as previously discussed, the empirically based sediment tPCB concentration estimate is suspected to be biased high due to the non-random study designs and sample depths greater than 3 cm reflecting deeper, more contaminated sediments upon which this estimate is based (King County 2013d). Therefore, the hindcast model based estimate may be more accurate than the comparison to the observed sediment data suggest.

According to hindcast testing of the fate model, the response time for Lake Washington sediment and water concentrations to reach equilibrium with a constant load is approximately 40 years. The most rapid change in concentrations occurs in the first 20 years. This suggests any changes reducing PCB load to Lake Washington will require several decades to be fully reflected in fish tissues.

The fate model was found to be very sensitive to log K_{ow} (octanol-water partitioning coefficient) and tPCB loads. When these inputs were varied in the uncertainty analysis both independently and together, it was determined that tPCB loading estimates contributed more to model prediction uncertainty than log K_{ow}.

Tissue concentrations predicted using water and sediment tPCB concentrations from field data compared to those using the fate model output demonstrated good performance of the bioaccumulation model with both, but better performance using the sediment and water concentrations predicted by the fate model.[18]. This was expected based on the suspected high bias in observed sediment tPCB concentrations. Model bias using the fate model output indicated the bioaccumulation model performed well and similar to applications of this model in San Francisco Bay, Georgia Basin and Puget Sound (Gobas and Arnot 2005, Condon 2007, Pelletier and Mohamedali 2009).

[18] Field data were likely biased high because sampling often focused on areas suspected of contamination (e.g., near combined sewer overflows or storm drains) and included samples that represented up to 10 cm of surface sediment, which potentially includes higher tPCB concentrations that occurred in sediments deposited in the 1970s. Because of this bias and better model fit of the fate model predicted sediment and water concentrations, the latter source was selected for use in model application occurring later in the project.

Log K_{ow}, water and sediment tPCB concentrations, lipid assimilation efficiency in fish and crayfish, and water fractions in copepods, amphipods/isopods, and daphnids were identified as the most sensitive inputs to the bioaccumulation model. The uncertainty analysis determined these parameters collectively contributed more uncertainty below than above the best estimate. The range in observed tissue concentrations is greater than the range in predicted concentrations associated with key model inputs for longfin smelt, large prickly sculpin, peamouth, smallmouth bass, cutthroat trout and northern pikeminnow.

While model performance testing indicated the fate and bioaccumulation models perform well for the purposes of this project, additional efforts could further improve model performance. The following efforts are recommended to reduce uncertainty in model predictions and observation data used in model testing if future efforts aim to improve model performance.

- Improve the empirically based estimate of mean sediment tPCB concentration by implementing a sediment sampling study with a random sampling design that focuses on the active sediment layer.
- Reduce uncertainty in log K_{ow} by analyzing a relatively small number of sediment and fish tissue samples for PCB congeners, composited for efficiency.
- Reduce uncertainty in observed fish tissue concentrations for smallmouth bass, prickly sculpin and northern pikeminnow by collecting more whole-body samples for PCB Aroclor® analysis.
- Fish eggs and larvae are key prey items for longfin smelt, threespine stickleback, and yellow perch. The accuracy of the modeled food web could be improved with further dietary studies and characterization of these prey items (i.e., mean lipid content, body mass, water fraction).

If seasonality or more spatial resolution is found to be relevant/necessary for management decisions, a two-layer, seasonally varying fate and bioaccumulation model could be developed predicated on the collection of higher resolution PCB data in time (e.g., monthly) and space (e.g., epilimnion\hypolimnion or nearshore\offshore). Also, with the addition of a vertical one dimensional sediment compartment, a time history of PCB inputs to the lake could be developed and used to calibrate the model to reproduce the history of sediment PCB accumulation.

In conclusion, the task of fate and bioaccumulation model development for application in subsequent steps of this project was completed. In the next phase of this project, the fate and bioaccumulation models will be coupled to test total tPCB loading reduction scenarios to inform water quality managers and stakeholders on the magnitude of change required for Lake Washington fish to reach safe levels of tPCBs and eliminate the consumption advisory. The results of these model simulations, along with a review of project findings and overall recommendations for future work, will be presented in a separate and final report for this project.

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Appendix A. Tissue Solids and Derived Moisture Data

Species	# Fish	Fork Length (mm)	Total Length (mm)	Weight (g)	% Solids	% Moisture (derived)	Source
Crayfish	1	58.4	119.5	45.92	24.8	75.2	McIntyre (unpublished)
Cutthroat Trout	1	182.0	220.2	60.00	19.7	80.3	McIntyre (unpublished)
Cutthroat Trout	1	195.0	232.3	80.00	21.9	78.1	McIntyre (unpublished)
Cutthroat Trout	1	211.0	247.2	92.00	23.0	77.0	McIntyre (unpublished)
Cutthroat Trout	1	188.0	225.8	80.00	23.2	76.8	McIntyre (unpublished)
Cutthroat Trout	1	262.0	294.6	168.00	24.5	75.5	McIntyre (unpublished)
Cutthroat Trout	1	250.0	283.5	154.00	25.0	75.0	McIntyre (unpublished)
Cutthroat Trout	1	251.0	284.4	174.00	25.1	74.9	McIntyre (unpublished)
Cutthroat Trout	1	402.0	418.0	656.00	25.2	74.8	McIntyre (unpublished)
Cutthroat Trout	1	317.0	350.0	332.00	26.9	73.1	McIntyre (unpublished)
Cutthroat Trout	1	358.0	383.9	552.00	28.9	71.1	McIntyre (unpublished)
Cutthroat Trout	1	442.0	462.1	958.00	29.4	70.6	McIntyre (unpublished)
Cutthroat Trout	1	395.0	418.4	710.00	31.1	68.9	McIntyre (unpublished)
Cutthroat Trout	1	427.0	448.1	908.00	31.6	68.4	McIntyre (unpublished)
Cutthroat Trout	1	426.0	445.0	1070.00	32.6	67.4	McIntyre (unpublished)
Cutthroat Trout	1	443.0	467.0	1118.00	32.7	67.3	McIntyre (unpublished)
Cutthroat Trout	1	375.0	398.0	726.00	33.6	66.4	McIntyre (unpublished)
Cutthroat Trout	1	480.0	500.0	1660.00	35.0	65.0	McIntyre (unpublished)
Daphnia	C	N/A	1	7.18	7.21	92.8	McIntyre (unpublished)
Daphnia	C	N/A	1	10.30	7.85	92.2	McIntyre (unpublished)
Daphnia	C	N/A	1	15.93	7.34	92.7	McIntyre (unpublished)
Daphnia	C	N/A	1	33.55	7.54	92.5	McIntyre (unpublished)
Daphnia	C	N/A	1	30.42	7.68	92.3	McIntyre (unpublished)
Daphnia	C	N/A	1	30.28	8.72	91.3	McIntyre (unpublished)
Longfin Smelt	C	N/A	52.8	0.49	15.9	84.1	McIntyre (unpublished)
Longfin Smelt	C	96.4	104.0	6.68	21.5	78.5	McIntyre (unpublished)
Longfin Smelt	C	92.0	99.4	5.98	23.2	76.8	McIntyre (unpublished)
Longfin Smelt	C	N/A	79.5	1.88	24.2	75.8	McIntyre (unpublished)
Longfin Smelt	1	125.6	135.0	17.70	29.1	70.9	McIntyre (unpublished)
Longfin Smelt	C	98.4	106.2	4.88	29.3	70.7	McIntyre (unpublished)
Mysids	C	N/A	10	2.81	17.2	82.8	McIntyre (unpublished)
Mysids	C	N/A	10	2.54	15.8	84.2	McIntyre (unpublished)
Mysids	C	N/A	10	2.44	15.9	84.1	McIntyre (unpublished)
Mysids	C	N/A	10	N/A	14.1	85.9	McIntyre (unpublished)
Mysids	C	N/A	10	N/A	14.7	85.3	McIntyre (unpublished)
Mysids	C	N/A	10	N/A	15.4	84.6	McIntyre (unpublished)
Mysids	C	N/A	N/A	N/A	14.3	85.7	McIntyre (unpublished)

Species	# Fish	Fork Length (mm)	Total Length (mm)	Weight (g)	% Solids	% Moisture (derived)	Source
Northern Pikeminnow	1	215.0	239.8	208.00	21.5	78.5	McIntyre (unpublished)
Northern Pikeminnow	1	178.0	198.0	58.00	21.7	78.3	McIntyre (unpublished)
Northern Pikeminnow	1	197.0	220.9	76.00	22.4	77.6	McIntyre (unpublished)
Northern Pikeminnow	1	218.0	242.9	102.00	22.5	77.5	McIntyre (unpublished)
Northern Pikeminnow	1	250.0	276.4	190.00	22.6	77.4	McIntyre (unpublished)
Northern Pikeminnow	1	185.0	N/A	62.00	23.2	76.8	King County (unpublished)
Northern Pikeminnow	1	190.0	216.0	82.00	24.8	75.2	McIntyre (unpublished)
Northern Pikeminnow	1	175.0	N/A	62.00	25.5	74.5	King County (unpublished)
Northern Pikeminnow	1	205.0	229.3	55.00	26.1	73.9	McIntyre (unpublished)
Northern Pikeminnow	1	190.0	N/A	68.00	26.2	73.8	King County (unpublished)
Northern Pikeminnow	1	205.0	N/A	112.00	26.6	73.4	King County (unpublished)
Northern Pikeminnow	3	385.0	N/A	543.33	27.0	73.0	King County (unpublished)
Northern Pikeminnow	1	370.0	401.9	658.00	27.1	72.9	McIntyre (unpublished)
Northern Pikeminnow	5	374.0	N/A	561.60	27.5	72.5	King County (unpublished)
Northern Pikeminnow	1	205.0	N/A	92.00	27.7	72.3	King County (unpublished)
Northern Pikeminnow	1	408.0	441.6	802.00	28.1	71.9	McIntyre (unpublished)
Northern Pikeminnow	3	380.0	N/A	604.67	28.5	71.5	King County (unpublished)
Northern Pikeminnow	1	413.0	446.9	726.00	28.6	71.4	McIntyre (unpublished)
Northern Pikeminnow	1	270.0	297.3	218.00	28.6	71.4	McIntyre (unpublished)
Northern Pikeminnow	1	395.0	428.0	678.00	28.9	71.1	McIntyre (unpublished)
Northern Pikeminnow	4	348.8	N/A	488.50	29.2	70.8	King County (unpublished)
Northern Pikeminnow	1	250.0	276.4	172.00	29.8	70.2	McIntyre (unpublished)

Species	# Fish	Fork Length (mm)	Total Length (mm)	Weight (g)	% Solids	% Moisture (derived)	Source
Northern Pikeminnow	5	416.0	N/A	794.00	30.6	69.4	King County (unpublished)
Northern Pikeminnow	5	472.0	N/A	1158.80	30.7	69.3	King County (unpublished)
Northern Pikeminnow	1	499.2	537.0	1320.00	31.1	68.9	McIntyre (unpublished)
Northern Pikeminnow	1	418.0	452.1	784.00	32.1	67.9	McIntyre (unpublished)
Northern Pikeminnow	1	387.0	419.7	668.00	32.2	67.8	McIntyre (unpublished)
Northern Pikeminnow	1	392.0	427.0	762.00	32.2	67.8	McIntyre (unpublished)
Northern Pikeminnow	1	430.0	464.7	950.00	34.1	65.9	McIntyre (unpublished)
Northern Pikeminnow	1	530.0	568.0	1720.00	34.2	65.8	McIntyre (unpublished)
Peamouth Chub	3	241.7	N/A	183.33	27.9	72.1	King County (unpublished)
Peamouth Chub	3	291.7	N/A	307.33	29.5	70.5	King County (unpublished)
Peamouth Chub	3	260.0	N/A	239.33	30.0	70.0	King County (unpublished)
Peamouth Chub	3	300.0	N/A	333.33	30.0	70.0	King County (unpublished)
Peamouth Chub	3	285.0	N/A	301.33	30.3	69.7	King County (unpublished)
Peamouth Chub	3	296.7	N/A	342.00	30.9	69.1	King County (unpublished)
Peamouth Chub	3	308.3	N/A	345.33	31.2	68.8	King County (unpublished)
Peamouth Chub	3	280.0	N/A	278.00	32.3	67.7	King County (unpublished)
Peamouth Chub	3	285.0	N/A	322.67	32.8	67.2	King County (unpublished)
Prickly Sculpin	C	N/A	30.7	0.29	18.8	81.2	McIntyre (unpublished)
Prickly Sculpin	1	N/A	122.0	20.62	19.4	80.6	McIntyre (unpublished)
Prickly Sculpin	C	N/A	33.5	0.40	19.4	80.6	McIntyre (unpublished)
Prickly Sculpin	1	N/A	135.5	29.00	19.6	80.4	McIntyre (unpublished)
Prickly Sculpin	1	N/A	127.5	25.63	20.0	80.0	McIntyre (unpublished)
Prickly Sculpin	C	N/A	32.4	0.36	20.1	79.9	McIntyre (unpublished)
Prickly Sculpin	C	N/A	95.2	9.20	20.7	79.3	McIntyre (unpublished)
Prickly Sculpin	C	N/A	30.2	0.28	20.9	79.1	McIntyre (unpublished)
Prickly Sculpin	C	N/A	102.5	11.43	21.0	79.0	McIntyre (unpublished)

Species	# Fish	Fork Length (mm)	Total Length (mm)	Weight (g)	% Solids	% Moisture (derived)	Source
Prickly Sculpin	1	N/A	130.0	22.45	21.7	78.3	McIntyre (unpublished)
Prickly Sculpin	1	N/A	128.5	22.01	21.7	78.3	McIntyre (unpublished)
Prickly Sculpin	C	N/A	101.7	11.01	21.7	78.3	McIntyre (unpublished)
Prickly Sculpin	C	N/A	93.2	10.04	22.1	77.9	McIntyre (unpublished)
Prickly Sculpin	C	N/A	98.0	9.66	22.5	77.5	McIntyre (unpublished)
Prickly Sculpin	1	N/A	126.0	21.16	22.8	77.2	McIntyre (unpublished)
Prickly Sculpin	1	N/A	167.0	51.46	23.6	76.4	McIntyre (unpublished)
Prickly Sculpin	75	N/A	< 20	N/A	18.5	81.5	King County (unpublished)
Prickly Sculpin	75	N/A	< 20	N/A	18.7	81.3	King County (unpublished)
Prickly Sculpin	20	N/A	> 20	N/A	23.8	76.2	King County (unpublished)
Smallmouth Bass	1	265.0	N/A	336.00	27.7	72.3	King County (unpublished)
Smallmouth Bass	1	325.0	N/A	690.00	27.7	72.3	King County (unpublished)
Smallmouth Bass	1	255.0	N/A	268.00	27.9	72.1	King County (unpublished)
Smallmouth Bass	1	315.0	N/A	528.00	29.1	70.9	King County (unpublished)
Smallmouth Bass	1	290.0	N/A	486.00	29.9	70.1	King County (unpublished)
Smallmouth Bass	1	428.0	465.7	1540.00	31.3	68.7	McIntyre (unpublished)
Smallmouth Bass	1	373.0	405.8	1166.00	31.7	68.3	McIntyre (unpublished)
Smallmouth Bass	1	354.0	385.2	1034.00	32.2	67.8	McIntyre (unpublished)
Sockeye Salmon (juv.)	C	103.4	114.1	N/A	21.2	78.8	McIntyre (unpublished)
Sockeye Salmon (juv.)	C	109.4	121.7	N/A	22.4	77.6	McIntyre (unpublished)
Sockeye Salmon (juv.)	C	111.0	123.7	N/A	22.6	77.4	McIntyre (unpublished)
Sockeye Salmon (juv.)	C	111.6	124.5	13.70	29.7	70.3	McIntyre (unpublished)
Sockeye Salmon (juv.)	C	113.4	126.8	15.90	29.8	70.2	McIntyre (unpublished)
Sockeye Salmon (juv.)	C	106.4	117.9	12.90	30.5	69.5	McIntyre (unpublished)
Threespine Stickleback	C	N/A	N/A	N/A	28.7	71.3	McIntyre (unpublished)
Threespine Stickleback	C	N/A	71.5	3.74	29.4	70.6	McIntyre (unpublished)

Species	# Fish	Fork Length (mm)	Total Length (mm)	Weight (g)	% Solids	% Moisture (derived)	Source
Threespine Stickleback	C	N/A	72.1	3.87	30.0	70.0	McIntyre (unpublished)
Threespine Stickleback	C	N/A	70.9	3.63	30.5	69.5	McIntyre (unpublished)
Trichoptera Larvae	C	N/A	23	0.36	31.3	68.7	McIntyre (unpublished)
Trichoptera Larvae	C	N/A	23	0.34	31.7	68.3	McIntyre (unpublished)
Trichoptera Larvae	C	N/A	23	0.34	32.6	67.4	McIntyre (unpublished)
Trichoptera Larvae	C	N/A	21	0.31	29.6	70.4	McIntyre (unpublished)
Trichoptera Larvae	C	N/A	21	0.27	28.6	71.4	McIntyre (unpublished)
Trichoptera Larvae	C	N/A	21	0.30	31.8	68.2	McIntyre (unpublished)
Trichoptera Larvae	C	N/A	22	0.29	30.5	69.5	McIntyre (unpublished)
Yellow Perch	1	126.4	130.0	24.67	19.6	80.4	McIntyre (unpublished)
Yellow Perch	1	141.7	146.0	30.34	20.3	79.7	McIntyre (unpublished)
Yellow Perch	1	143.6	148.0	35.00	21.3	78.7	McIntyre (unpublished)
Yellow Perch	1	153.1	158.0	45.55	21.4	78.6	McIntyre (unpublished)
Yellow Perch	1	119.7	123.0	15.98	22.2	77.8	McIntyre (unpublished)
Yellow Perch	1	137.8	142.0	27.02	22.4	77.6	McIntyre (unpublished)
Yellow Perch	1	127.4	131.0	20.94	23.0	77.0	McIntyre (unpublished)
Yellow Perch	1	124.5	128.0	18.92	24.0	76.0	McIntyre (unpublished)
Yellow Perch	1	134.0	138.0	26.38	24.2	75.8	McIntyre (unpublished)
Yellow Perch	1	227.0	235.0	151.30	27.9	72.1	McIntyre (unpublished)
Yellow Perch	1	254.0	262.0	240.00	28.1	71.9	McIntyre (unpublished)
Yellow Perch	1	222.0	231.0	163.70	29.0	71.0	McIntyre (unpublished)
Yellow Perch	1	233.0	242.0	178.00	29.0	71.0	McIntyre (unpublished)
Yellow Perch	1	240.0	249.0	183.30	29.0	71.0	McIntyre (unpublished)
Yellow Perch	1	227.0	237.0	144.40	29.5	70.5	McIntyre (unpublished)
Yellow Perch	1	318.0	330.7	474.00	29.7	70.3	McIntyre (unpublished)
Yellow Perch	1	269.5	280.0	255.00	29.9	70.1	McIntyre (unpublished)
Yellow Perch	1	260.0	271.0	268.00	30.3	69.7	McIntyre (unpublished)
Yellow Perch	1	262.8	273.0	N/A	30.5	69.5	McIntyre (unpublished)
Yellow Perch	1	229.0	236.0	163.20	30.7	69.3	McIntyre (unpublished)
Yellow Perch	1	320.0	332.8	516.00	31.0	69.0	McIntyre (unpublished)
Yellow Perch	1	298.1	310.0	444.00	31.1	68.9	McIntyre (unpublished)
Yellow Perch	1	224.0	233.0	141.90	31.2	68.8	McIntyre (unpublished)
Yellow Perch	1	290.0	301.4	354.00	31.3	68.7	McIntyre (unpublished)
Yellow Perch	1	230.0	239.0	172.50	32.0	68.0	McIntyre (unpublished)
Yellow Perch	1	298.1	310.0	468.00	32.0	68.0	McIntyre (unpublished)
Yellow Perch	1	282.0	293.0	342.00	32.3	67.7	McIntyre (unpublished)
Yellow Perch	1	290.0	302.0	382.00	33.3	66.7	McIntyre (unpublished)

Species	# Fish	Fork Length (mm)	Total Length (mm)	Weight (g)	% Solids	% Moisture (derived)	Source
Zooplankton	C	N/A	1	26.00	10.7	89.3	McIntyre (unpublished)
Zooplankton	C	N/A	1	N/A	11.1	88.9	McIntyre (unpublished)
Zooplankton	C	N/A	1	N/A	12.3	87.7	McIntyre (unpublished)
Zooplankton	C	N/A	N/A	46.00	10.1	89.9	McIntyre (unpublished)
Zooplankton	C	N/A	1	13.00	11.8	88.2	McIntyre (unpublished)
Zooplankton	C	N/A	1	20.00	10.4	89.6	McIntyre (unpublished)

N/A – not measured
C - Composite sample
juv - Juvenile
Trichoptera Larvae used for benthic macroinvertebrate estimates
Zooplankton used for copepod, isopod and amphipod estimates

Appendix B. Volume-weighted Average Parameter Calculations

		Average Measurements						Volume-Weighted Measurements				
Depth (m)	**Volume[a] (m3)**	**DOC (mg/L)**	**DO (mg/L)**	**Temp (°C)**	**TOC (mg/L)**	**TSS (mg/L)**		**DOC (mg)**	**DO (mg)**	**Temp (°C)**	**TOC (mg)**	**TSS (mg)**
< 5	4.21E+08	3.18	10.11	14.3	3.53	1.22		1.34E+09	4.25E+09	6.0E+09	1.48E+09	5.13E+08
5 to 10	3.84E+08		9.94	14.4		1.22			3.82E+09	5.5E+09		4.70E+08
10 to 15	3.51E+08		9.20	13.1		0.97			3.23E+09	4.6E+09		3.39E+08
15 to 20	3.23E+08		8.95	10.6		0.83			2.89E+09	3.4E+09		2.69E+08
20 to 25	2.95E+08		9.24	9.3		0.84			2.72E+09	2.7E+09		2.49E+08
25 to 30	2.67E+08		9.18	8.7					2.46E+09	2.3E+09		
30 to 35	2.30E+08		9.09	8.4					2.09E+09	1.9E+09		
35 to 40	1.91E+08		8.95	8.1		0.81			1.71E+09	1.6E+09		1.54E+08
40 to 45	1.57E+08	3.07	8.87	8.0	3.46	0.89		4.81E+08	1.39E+09	1.3E+09	5.42E+08	1.39E+08
45 to 50	1.21E+08	2.94	8.43	7.8	3.21	0.89		3.57E+08	1.02E+09	9.4E+08	3.89E+08	1.08E+08
50 to 55	9.15E+07	3.02	8.59	7.8	3.08	1.16		2.76E+08	7.86E+08	7.1E+08	2.82E+08	1.06E+08
55 to 60	4.69E+07	2.91	8.06	7.6	3.10	1.20		1.37E+08	3.78E+08	3.6E+08	1.45E+08	5.62E+07
60 to 65	7.28E+06	3.06	7.67	7.7	3.21	1.76		2.23E+07	5.59E+07	5.6E+07	2.34E+07	1.28E+07
						Sum of Volume-Weighted Measurements		2.61E+09	2.68E+10	3.1E+10	2.87E+09	2.42E+09
						Sum of Volume (representative of measurement depths)		8.45E+08	2.89E+09	2.9E+09	8.45E+08	2.39E+09
						Volume-Weighted Average Measurements		**3.09**	**9.29**	**10.9**	**3.39**	**1.01**

[a] Volumes from Barnes (1976) p. 40

Appendix C. Bioaccumulation Model Sensitivity Analysis Results

(see separate PDF file)